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DEVELOPMENT OF FRAMEWORK FOR STATEWIDE VEHICLE MILES TRAVELED (VMT) ESTIMATION

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DEVELOPMENT OF FRAMEWORK FOR STATEWIDE VEHICLE MILES TRAVELED (VMT) ESTIMATION

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of

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Trevor J. Klatko

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For my parents and grandparents.

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ACRONYMS AND ABBREVIATIONS

AADT	Average Annual Daily Traffic
ATR	Automatic Traffic Recorder
AVMT	Annual Vehicle Miles Traveled
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
BMV	Bureau of Motor Vehicles
CAAA-90	Clean Air Act Amendments
CRHV	County Roads High Volume
CRLV	County Roads Low Volume
CSHV	City Streets High Volume
CSLV	City Streets Low Volume
CT	Combination Trucks
EGR	Economic Growth Region
EIA	Energy Information Administration
FC	Functional Classification
FHWA	Federal Highway Administration
GF	Growth Factor
GIS	Geographic Information System
GVW	Gross Vehicle Weight
HPMS	Highway Performance Monitoring System
HS	Highway Statistics
HSIP	Highway Safety Improvement Program
HTF	Highway Trust Fund
INDOT	Indiana Department of Transportation

IMP	Interstate Maintenance Program
ISTEA-99	Intermodal Surface Transportation Efficiency Act
LRS	Location Referencing System
MAP-21	Moving Ahead for Progress in the 21st Century Act
MACOG	Michiana Area Council of Governments
MPO	Metropolitan Planning Organization
NHS	National Highway System
NHTS	National Household Travel Survey
NN	Natural Neighbor
OHPI	Office of Highway Policy Information
RPO	Regional Planning Organization
SHS	State Highway System
SHA	State Highway Agency
SUT	Single-Unit Trucks
STP	Surface Transportation Program
STT	Single-Trailer Trucks
TAPC	Tippecanoe Area Plan Commission
TCDS	Traffic Count Database System
TDM	Travel Demand Model
UAB	Urban Area Boundaries
USC	United States Census
USDOT	United States Department of Transportation
VC	Vehicle Classification
VMT	Vehicle Miles of Travel or Vehicle Miles Traveled
WIM	Weigh-in-Motion

ABSTRACT

Klatko, Trevor J., M.S.C.E., Purdue University, December 2015. Development of Framework for Statewide Vehicle Miles Traveled (VMT) Estimation. Major Professor: Dr. Samuel Labi.

Vehicle Miles Traveled (VMT) is a critical performance measure that is used extensively in highway transportation management for financial analysis, resource allocation, impact assessments, and reporting to oversight agencies. As highway revenue from fuel taxes continues to plummet and user-based taxes such as VMT fees become increasingly attractive, consistent and reliable VMT estimates have become critical for highway funding evaluation and administration. At the present time, there are several methods for VMT estimation that typically yield estimates that are inconsistent or inaccurate. This thesis presents alternative techniques for VMT estimation in the state of Indiana at the project, regional, and network levels for confirming or estimating the levels and distribution of vehicular travel at the present time as well as at any specified future time. The present research also developed a benchmark method (segment-level using traffic counts) for VMT estimation and shows how the estimates from the other different methods can be calibrated to mitigate the inconsistencies in statewide VMT estimation across the different methods. The early tasks of the research, which included a literature review and survey of VMT-data stakeholders, helped streamline the research effort, categorize the different techniques for VMT estimation and identify their limitations, and identified the preferred outputs of any platform for VMT estimation.

The core outcome of this thesis is a comprehensive framework for estimating the VMT contributed by each vehicle class for the state's entire road network. This framework estimates statewide VMT by using the segment length, traffic volume, and distance, for the primary highway systems of state routes (interstates and US and state

roads) and local routes (city streets and county roads). Local route VMTs were studied in-depth because of their historical underrepresentation in VMT studies, the low accuracy of past estimating methods, and the local road's significant share of the total road inventory. For the state road VMT estimation, a comprehensive database was developed that facilitates extensive aggregations of VMT by geographical scope, route, functional class, and vehicle class. For the local-route VMT estimation, a sample of counties of different spatial locations and degrees of urbanization were used. Analytical techniques and tools, including cluster analysis, geographic information systems (GIS), and spatial interpolation techniques were used to expand the VMT estimates from the local road sample to the population of all counties in the state.

The results indicate that there is a -21% (underestimate) to +8 % (overestimate) in the results from the various VMT estimation methods, as compared to the benchmark method (segment-level VMT estimation) developed in this research. The technique developed in this research for reconciling these different VMT estimates was validated using the estimate from the benchmark method as a basis. The implementation platform developed in this research was designed to produce outcomes that address the VMT data needs of a state highway agency and other stakeholders, and could be enhanced in the future as and when data become available. The deliverables from this research are expected to have far-reaching impacts on the various functional areas of highway management and administration, the evaluation of a VMT fee as an alternative or complement to the fuel tax for highway revenue, and the generation of required reports to federal oversight agencies.

CHAPTER 1. INTRODUCTION

1.1 Background and Motivation

Vehicle miles of travel (VMT) estimates are used extensively for a variety of highway transportation management functions, including asset management, financial analysis, resource allocation planning, estimation of emissions and energy consumption, and traffic impact assessments, as shown in Figure 1.1. VMT serves as a critical input for these wide range of applications for the following reasons.

First, reliable estimates or predictions of VMT are critical for estimating or predicting highway revenue levels. For example, highway revenue forecasting models rely on VMT by vehicle class in future years to estimate possible revenue scenarios. Second, reliable VMT data are integral to the reporting of highway asset performance in terms of system preservation, congestion mitigation, safety, and mobility. For example, network-wide safety performance is often measured in terms of the number of fatalities per million VMT. Third, VMT data is useful for high-level oversight of a transportation system and also for investigating the impacts of changes in policy. State legislatures often make requests for aggregate travel information (VMT by vehicle class and highway class) on the state highway network, particularly in the current era when states have begun to consider legislation related to new or existing revenue sources. Fourth, due to current and projected sharp reductions in fuel tax revenue, state and federal governments are considering the feasibility of switching from the current fuel tax to a mileage-based user tax such as a VMT fee. State highway agencies (SHA) need the capability to generate reliable and consistent VMT estimates and VMT forecasts in order to estimate the expected revenue from any mileage-based user fees in the future. Fifth, as evidenced by past trends, there appears to be a strong and positive correlation between VMT and the economic output of a region, and VMT values therefore can potentially serve as a gauge of the economic output in a state.

For the reasons stated above, VMT data are used by state transportation agencies, metropolitan planning organizations (MPOs), regional planning organizations (RPOs), local municipalities, and federal agencies and legislators for a variety of business processes and functions (Figure 1.1), including financial analysis (revenue predictions from fuel tax, VMT-based user fees, etc.), submission of annual reports to the Federal Highway Administration (FHWA), transportation planning, highway cost allocation (attribution of consumption costs, etc.), measuring the health of the regional economy and the impact of interventions, network-level asset management, environmental and energy impact assessments, and evaluation of the operational impact investments in terms of safety and mobility (EPA, 1999; Fricker and Kumapley, 2002; Gunawardena and Sinha, 1994; Kumapley and Fricker, 1994; Varma et al., 1992).

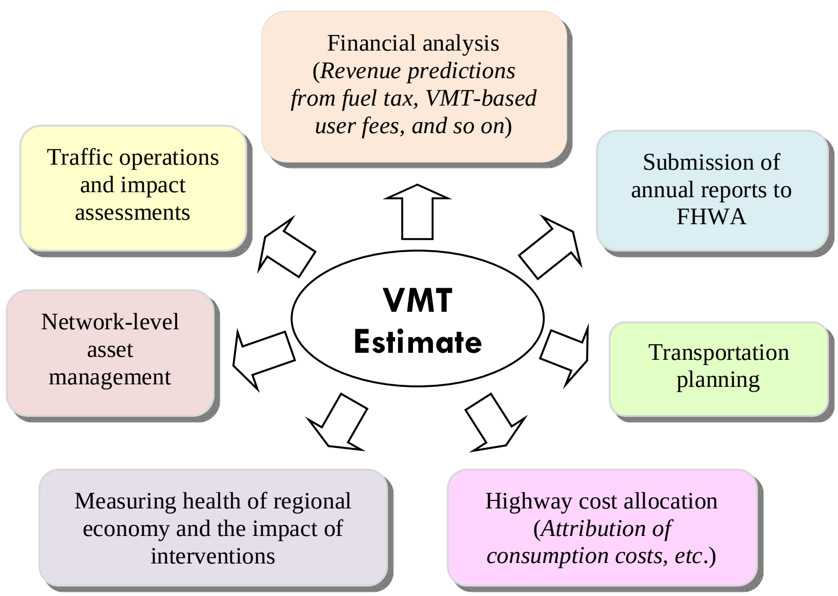


Figure 1.1 Applications of VMT estimates in highway agencies

VMT has critical implications for highway funding as well, because VMT levels influence each state's "share" of federal highway funding. The funding provided by the

Interstate Maintenance Program (IMP), the National Highway System (NHS), the Surface Transportation Program (STP), and the Highway Safety Improvement Program (HSIP) is allocated, in part, using a formula relating the extent of the VMT on the appropriate highway system. For example, apportionment formulas for federal-aid eligible highway programs including the IMP, NHS, STP, and HSIP, have weights of 33.33%, 35.00%, 40.00%, and 33.33%, respectively, based on the VMT (FHWA, 2014).

Within transportation planning and the decision-making process, VMT information assists in the compliance process for federal regulations and legislation. The Clean Air Act Amendments of 1990 (CAAA), the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA-91), the Transportation Equity Act for the 21st Century (TEA-21), SAFETEA-LU of 2005, and most recently, MAP-21 all require VMT to varying extents. As seen from Figure 1.2, each legislation has provisions that implicitly require VMT estimations (Fricker and Kumapley, 2002; Office of Highway Policy Information (OHPI), 2014a; Vadlamani, 2005). Because the basis for compliance and funding is often the highway categories or functional classes, accurately reporting VMT is important.

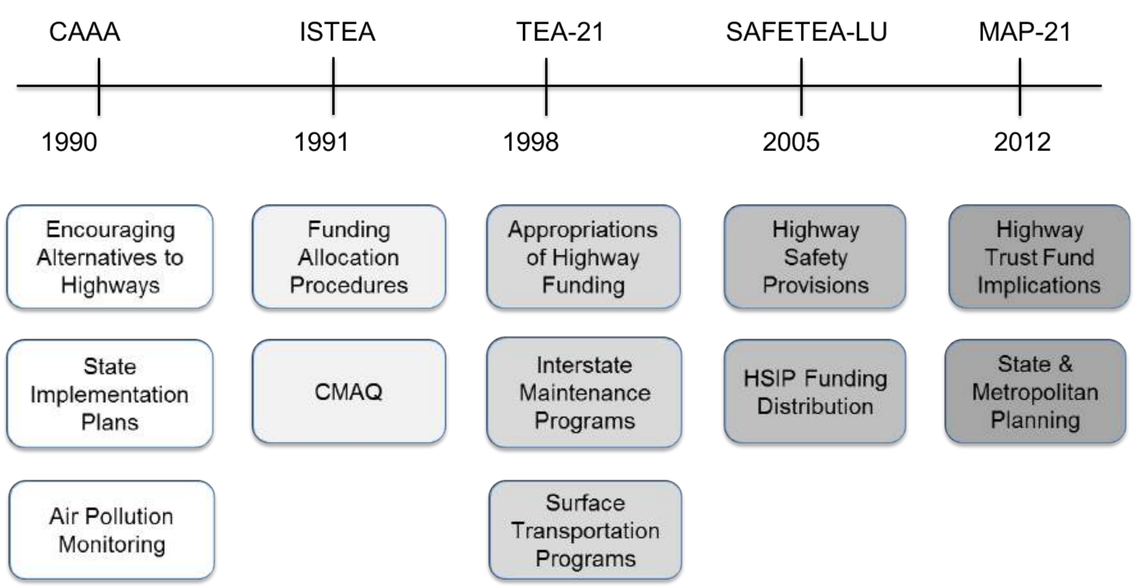


Figure 1.2 Timeline of federal legislation that implicitly require VMT estimates

Appropriations of highway funding and IM and STP programs are affected by TEA-21. The IM program finances an essential range of projects, from routine upkeep of interstate HMA pavement overlays to inspections and geometric safety improvements to reduce crashes (Office of Highway Policy Information (OHPI), 2014a; b; Stanley et al., 2002). MAP-21 had major implications for the designation of roads as part of the National Highway System (NHS), with all principal arterials now designated as NHS routes. MAP-21 also affects highway trust funds and the state and metropolitan planning processes, which heavily rely on VMT estimates as critical inputs.

1.2 Problem Statement

VMT estimates typically come from a wide variety of sources, with significant variation among the estimates from these sources. In theory, the VMT estimates from disaggregate methods should add up to yield a reported aggregate value; however, in practice, the sum of the disaggregate VMT is not always equal to the aggregate total VMT. Such inconsistency is a particularly worrisome situation because VMT plays a critical role in INDOT's tactical and strategic policy analysis and decision-making.

For each method of VMT estimation, different sample sizes, computational techniques, and resource levels can be used to satisfy the intended end-use. Different assumptions and techniques affect the accuracy of each method. The unique level of aggregation of each method is important for INDOT processes. Currently, INDOT cannot readily provide VMT by vehicle class and highway functional class.

As a result, applications such as revenue predictions and attributions by vehicle class and highway class, asset deterioration, and operational performance associated with each vehicle class, are severely limited. While AADT/VMT estimation typically is used for transportation planning and traffic operations, there are many applications that are handicapped by the lack of a consistent and comprehensive VMT estimation framework.

Many states and the federal government are considering the feasibility of switching from the current fuel-based revenue source to a mileage-based user fee structure. Therefore, reliable and consistent VMT estimates and forecasts are needed to evaluate the potential impacts of switching to a mileage-based user fee. Proposed changes to the tax rates and revenue streams related to the state highway system (SHS) often rely on VMT studies to assist policymakers with these decisions.

1.3 Research Objectives and Scope

Considering the importance of VMT, an objective analysis of statewide VMT at all levels using different approaches is needed. This research seeks to outline the limitations and advantages of each approach, quantitatively assess the extent of deviation, identify a desirable option, and provide a practical framework for working with VMT information. The specific research objectives include the following:

1. Investigate alternative VMT estimation approaches in terms of accuracy and ease-of-computation and gauge the extent of deviation of the VMT estimates obtained from different approaches.
2. Develop a framework for reliable estimation and prediction of statewide VMT at the project and network levels that is easily adoptable and sustainable for INDOT business units.
3. Develop a spreadsheet tool to implement the framework. This tool will serve as a central source for summary outputs and will provide tabular and graphical results that aim to quantify existing VMT and highlight changing trends with VMT throughout the state.
4. Recommend an implementation and management strategy for storing and updating the VMT information contained in the spreadsheet tool that will enhance implementation and usage across INDOT.

The scope of the research is state and local routes that comprise Indiana's public highway system, which covers 90,000 miles. State routes are defined for this research as interstates (I), US highways (US), and state roads (SR), with all interstates designated as NHS, the majority of US highways as NHS, and some major state roads as NHS. The local routes, as defined for this research, are non-INDOT owned city streets (CS) and county roads (CR). City streets include avenues, boulevards, downtown streets, lanes, and other neighborhood streets.

1.4 Thesis Organization

This thesis is organized topically into six main chapters, each consisting of a major task of the research. Chapter 1 contains the preface and background information to introduce the topic of VMT in highway management as well as the problem statement and objectives. Chapter 2 presents the literature review of past studies related to VMT estimation, particularly approaches for VMT estimation and the methods within each approach that would be applicable at the state level. In Chapter 3, the research methodology is presented, including the framework for the research and the procedures applied to meet the research objectives. The main organization of VMT estimation by the link-level (traffic related) and non-link-level (non-traffic) is also discussed. Chapter 4 presents the analysis and modeling for state routes, local routes, and non-link-level methods of VMT estimation. Chapter 5 presents the results and discusses the statewide VMT aggregations for both estimation and prediction of state and local route VMT. Finally, Chapter 6 summarizes the research methodology and framework and discusses the conclusions and recommendations, the problems encountered, and the direction of future research.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Past comprehensive reviews of VMT estimation approaches (Fricker and Kumapley, 2002; Kumapley and Fricker, 1996; Liu and Kaiser, 2006; Vadlamani, 2005) have consistently emphasized two broad approaches that differ by input data types for statewide VMT estimation, as shown from Figure 2.1.

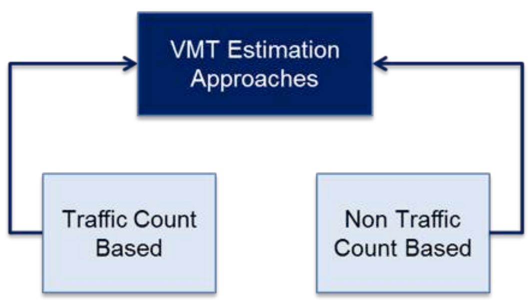


Figure 2.1 Broad approaches for statewide VMT estimation

The first school of thought supports a VMT estimation approach based on traffic counts of the road network. This approach is institutionalized in the FHWA's Highway Performance Monitoring System (HPMS) (Office of Highway Policy Information (OHPI), 2014a). The approach consists of taking traffic counts at different points along the road network and expanding that data based on the total road inventory associated with each sample point, to produce an area-wide VMT estimate based on the (Office of Highway Policy Information (OHPI), 2014c).

The second school of thought determines VMT based on non-traffic data sources, typically applicable for the network level. This non-traffic VMT estimation approach considers the location, sources, and purpose of the travel that influence statewide VMT. This is referred to as the VMT approach not based on traffic counts. In some cases, the aspects of this approach are indirectly related to traffic counts. The approach starts with indirect predictors of VMT, such as the number of households, household incomes, licensed drivers, and vehicle registrations. The obtained results from this approach are then validated by a comparison to actual ground traffic counts for a select number of count locations.

There are limitations and different resources required for each of these two approaches. This thesis seeks to highlight the qualitative and quantitative limitations and merits associated with each approach in order to identify the most desirable option for implementation within INDOT business units.

2.2 Characteristics of VMT Estimation Approaches

This section discusses the background and literature on the identified statewide VMT approaches based on traffic and non-traffic data sources. A summary of the key characteristics of the estimation approaches by data type and application level is provided herein.

2.2.1 VMT Estimation Using Traffic-Based Methods

In VMT estimation related to traffic counts, traffic volume is determined using continuously-collected traffic data for the population or sample of highway segments. Actual on-the-ground traffic counts are obtained at various times seasonally and daily, such as peak and off-peak hours, which intuitively are expected to be a reliable means to measure actual travel. SHAs often use this type of approach for planning, monitoring, and estimating purposes. After the HPMS was developed in 1978, SHAs have used the HPMS sample as a basis for their annual reporting to FHWA regarding their highway infrastructure operations, condition, and performance (EPA, 1999; Office of Highway Policy Information (OHPI), 2014a).

Part of the annual submission process to federal oversight agencies includes statewide VMT estimates. For this purpose, a sample of traffic counts for selected road segments is expanded based on the size of the roadway inventory associated with each sampling point in order to produce an area-wide or statewide VMT estimate by functional class (FHWA, 2013).

The HPMS mandates that all federal-aid eligible highway routes must have traffic volumes measured through count stations, to assess current and predict future traffic conditions (Office of Highway Policy Information (OHPI), 2014a). To accomplish this, annual average daily traffic (AADT), a common measure of traffic volume used extensively in this research, is estimated using both temporary and permanent traffic count stations.

Permanent count stations collect daily traffic data and are used to assess long-term changes occurring to a road system (Office of Highway Policy Information (OHPI), 2014b). These stations are equipped with automatic traffic recorders (ATR) to represent the population and maximize benefit. As of 2015, Indiana maintains 106 continuous, or permanent, traffic count stations. These traffic counts must often be adjusted to more accurately represent traffic conditions depending on the time of year and day of the week. Researchers have used a variety of techniques for adjusting AADT to more accurately represent traffic conditions, including neural networks and weighted-distance methods (Jin and Fricker, 2008; Sharma et al., 1999). The state of Indiana also has 44 weigh-in-motion (WIM) detectors that provide important traffic data used to develop ESAL values, temporal adjustments to short-term counts, identify long-term trends, and measure vehicle weights (Indiana Department of Transportation (INDOT), 2015a; b).

Short-term count stations, or temporary count stations, are coverage counts collected from rotational programs, typically collected at 2-3 year frequencies. The Statewide Coverage Count Program implemented by INDOT collects traffic counts for state owned routes and non-state owned Federal Aid Routes, with 10,000 and 6,000 counts required annually, for state owned routes and non-state owned Federal Aid Routes, respectively (Indiana Department of Transportation (INDOT), 2015a). The temporary stations collect at least 48 hours of traffic counts, which are subsequently averaged to 24 hours to produce AADT estimates and are then commonly used as inputs for VMT estimation and a multitude of other transportation planning applications from the project to network level ((Office of Highway Policy Information (OHPI), 2014b).

However, one of the reoccurring issues with traffic monitoring and thus VMT estimation, is the lack of count consistency and reliable coverage for local routes (Mohamad, 1997; Mohamad et al., 1998; Seaver et al., 2000). State routes, such as interstates, and US highways, typically have higher availability of traffic data than the local routes, such as city streets and county roads under the jurisdiction of local governments. The extent of data collected depends on the road classification, importance, and availability of traffic counting equipment. For example, interstates are extensively monitored, many with permanent ATRs capable of providing volume, classification, and weight data for each of the 13 FHWA vehicle classes. However, these types of counting stations are not as widely available.

One method, or a group of techniques for estimating VMT, is referred to as the link-level method (or segment-level) from traffic counts as shown in Figure 2.2. The link-level method can be based on actual or estimated counts, from either the population or a sample thereof. Travel demand models (TDMs) are an example of this approach, where the estimated counts are expanded to the road network to simulate traffic, often for project-level applications.

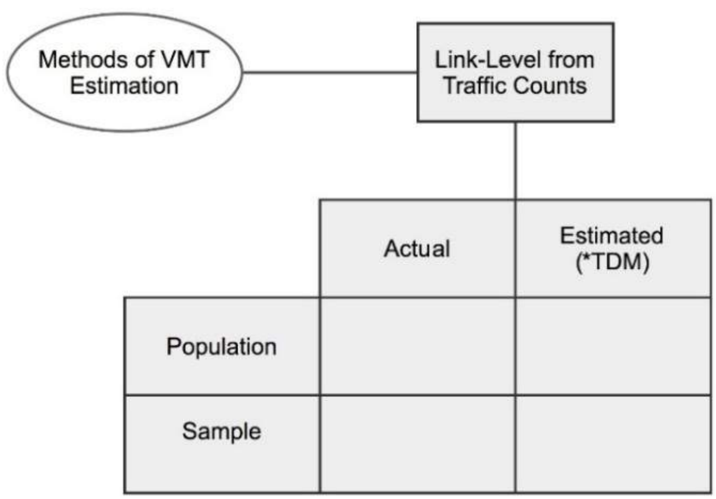


Figure 2.2 Hierarchy of link-level estimation from traffic counts

2.2.2 VMT Estimation Using Methods Not Based on Traffic Counts

The proposed VMT estimation approach uses methods that are not based on traffic counts. There are a number of different methods researchers have used, such as those based on driving age cohort and demographic characteristics, odometer readings, fuel sales, socioeconomic regression models, and vehicle registrations (Agbelie et al., 2010; Kumapley and Fricker, 1994; Maring, 1974; Schipper and Moorhead, 2000; Vasudevan and Nambisan, 2013). Over 20 years ago, it was realized that economic indicators, such as gasoline sales, income, employment, and vehicle registrations could be used as a basis for VMT estimation (Erlbaum, 1989). These non-traffic based methods apply relatively simple procedures to obtain aggregate VMT estimates based on socioeconomic, demographic, and travel indicators, which are correlated with VMT.

The need to combine, sort, and validate data is time-intensive and researchers (Fricker and Kumapley, 2002; Vadlamani, 2005) have noted these challenges. A particular challenge is the validation of the obtained results for local routes due to the general lack of consistent local road traffic counts. Similarly, demographics, household characteristics, economic activity, and fuel efficiencies are dynamic and certainly need to be updated for future years. Travel surveys, which are critical inputs for many non-traffic methods, such as the National Household Travel Survey (NHTS) (FHWA, 2009) and the U.S. Census (USC) (U.S. Census, 2010), are updated every five to six and ten years, respectively. Intermediate information is often not available for much of the non-traffic data, proving problematic and requiring interpolation or averaging prior years of data. The level of applications can also be limited by non-traffic-based approaches, with coarse aggregate estimates often the type of VMT estimate produced. Disaggregate data may be required in some cases, and non-traffic VMT estimation methods do not readily provide this level of application.

2.2.3 VMT Estimation Methods by Type of Data

The type of input data and procedures used for calculations distinguish the varying methods of VMT estimation. As presented in Figure 2.3, the main methods identified are capable of providing statewide coverage. However, certain methods, as discussed this section, can estimate VMT for all vehicle classes or for personal travel (non-commercial vehicles). In-state and out-of-state splits can be applied to aggregate statewide estimates to more accurately assess the amount of travel occurring within the given state.

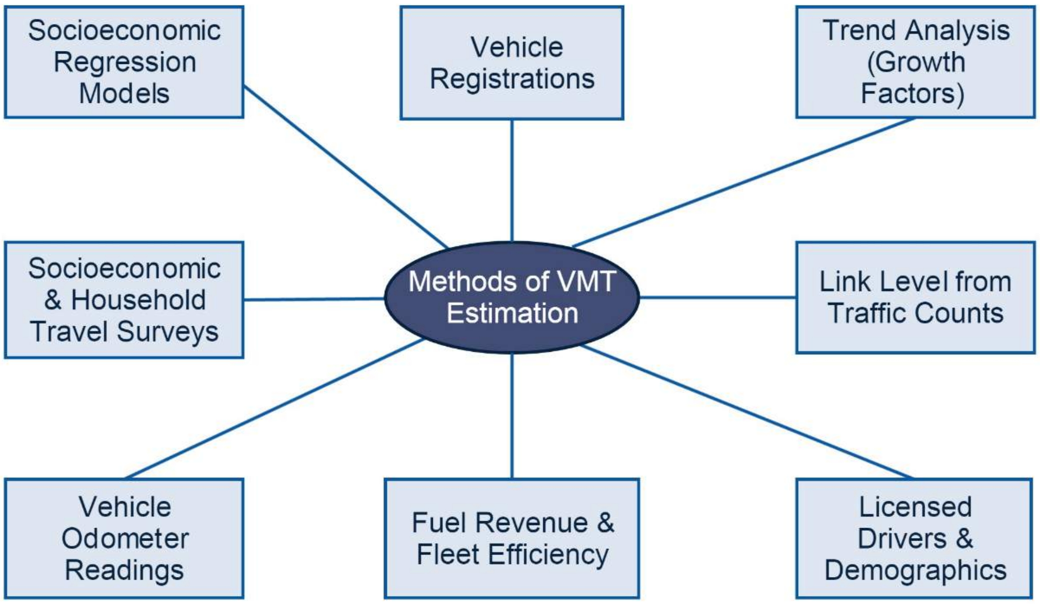


Figure 2.3 VMT estimation methods to provide statewide coverage

A matrix was developed to summarize the differences in the methods for VMT estimation based on the data type used. The characteristics of each VMT estimation method are presented in Figure 2.4. The type of method, coverage level, and data requirements also are indicated. These characteristics are important to understand in a qualitative sense before providing quantitative estimates because a method is inherently limited or enhanced based on these characteristics.

VMT Estimation Method \ Estimation Characteristic	Traffic-Based	Non-Traffic Based	Directly Obtainable By Functional Class	Directly Obtainable By Vehicle Class	Demographics Data	Fuel Tax Reports	Socioeconomic Data	Uses Growth Rates or Expansion Factors	Travel-Survey Based	Time Series Data
Trend Analysis (Growth Factors)	X	X						X		X
Regression Analysis		X		X			X			
Socioeconomic (Household) Travel Surveys		X			X		X		X	
Licensed Drivers & Demographics		X			X				X	X
Link Level (Sample - HPMS)	X		X					X		
Link Level (Actual - Population)	X		X	X						
Odometer Readings		X							X	
Fuel Usage & Fleet Effiencies		X				X				
Link Level (Estimated - TDM)	X	X					X	X		
Vehicle Registrations		X		X						

Figure 2.4 Summary matrix of VMT estimation approaches by data inputs

Different methods are not as useful for some end-users as others. Each VMT estimation method is more or less suitable, depending on the desired coverage level and application requested from the end-user. For example, if VMT is desired by vehicle classes for revenue forecasting models, then a link-level method and vehicle registrations may be most appropriate, depending on the availability of required data. Although other methods can indirectly determine VMT by vehicle classes, a lack of data and decreased reliability proves cumbersome for the producers of VMT information. Similarly, if fuel tax reports are available, then statewide VMT can be estimated by relating fuel usage and fleet efficiencies.

2.2.4 VMT Estimation Methods by Level of Coverage

The level of coverage required by the end-user, and whether it is at the project, regional or metropolitan, or statewide levels, greatly affects which VMT estimation approach is most appropriate.

As seen in Figure 2.5, link-level methods based on traffic counts provide the most coverage, from the project level to the network level. Providing the most coverage is desirable for the wide-range of agency applications that use VMT estimates.

Level of Coverage / VMT Estimation Method	Link or Project Level	Regional or Metropolitan Level	Statewide Level
Trend Analysis (Growth Factors)			X
Regression Analysis	X	X	X
Socioeconomic (Household) Travel Surveys		X	X
Licensed Drivers & Demographics			X
Link Level (Sample - HPMS)	X		X
Link Level (Actual - Population)	X	X	X
Odometer Readings			X
Fuel Usage & Fleet Efficiencies			X
Link Level (Estimated - TDM)	X	X	X
Vehicle Registrations			X

Figure 2.5 Methods for VMT estimation by level of coverage

Project-level detail (at the segment or link-level) may be required when the VMT of a specific corridor project is requested. For example, examining the trends in VMT for a specific route is important for safety or congestion management. Similarly, VMT estimates at a regional or metropolitan level may be required in the evaluation of changing trucking patterns across different economic regions. Also, if aggregation by highway functional class is what is needed, then VMT estimates from socioeconomic and licensed driver travel surveys do not fulfill this end use; in this case, the most appropriate method would be a link-level method.

Another method of VMT estimation, trend analysis, relies on historical data to predict future travel; therefore, sudden economic downtowns or upsurges may limit this approach and will increase the deviation of the estimated VMT from the actual values.

2.3 Literature Specific to Statewide VMT Estimation

While there has been much research on AADT/VMT estimation, the focus of this literature review centers on applications at the statewide level. The methods related to non-traffic and traffic inputs are examined in this section.

2.3.1 Methods of Non-Traffic Based Estimation

Early research on VMT estimation in the 1970s and 1980s (Greene, 1987; Maring, 1974) was based on using driving age population, licensed driver populations, and average annual mileage driven to forecast nationwide trends. Travel surveys, particularly the National Personal Transportation Survey (NPTS), which has since been renamed the National Household Travel Survey (NHTS) were available and demographic trends are key inputs for this method. Using the average annual miles by licensed drivers and the distribution by gender and age groups, the researchers generated a nationwide 2020 estimate. The results were not validated using VMT estimated from a traffic-based method. Building upon this work, a Purdue study (Kumapley and Fricker, 1994) developed two cross-classification models for Indiana to supplement INDOT's traffic-based VMT estimation. Their method addressed the sampling bias that typically accompanies traffic-based VMT estimation because functional classes are not used as inputs). An updated version (Fricker and Kumapley, 2002) concluded that the actual personal VMT was 5% lower than INDOT's estimate. The travel surveys used for developing personal VMT estimates were edited for errors; however, discrepancies still exist from travel surveys.

Demographic and licensed driver's data are compiled by the NHTS and FHWA's *Highway Statistics* series (Office of Highway Policy Information (OHPI), 2014d), along with data from the *American Fact Finder* specific to Indiana (US Census, 2010) for the inputs required for VMT estimation from these methods. These inputs typically include state population, population eligible to be licensed drivers, and annual mileage per licensed driver by the different age groups and sex. Total annual statewide VMT is estimated by multiplying the total annual VMT for both male and female drivers by the number of licensed drivers per capita and the population (Kumapley and Fricker, 1996).

The commercial or trucking component of VMT cannot be determined using driving age and demographic information because the travel survey inputs typically are gauging personal travel. Considering that Indiana has a significant amount of commercial traffic as many major interstates pass through the state, connecting major economic corridors such as Chicago to Indianapolis and Indianapolis to Columbus, the use of these methods to represent statewide VMT is particularly problematic and should be avoided.

Regression models have been applied to estimate VMT for a specific spatial area. On use of these models is estimating VMT for the highway section level (Eom et al., 2006; Mohammad, 1997; Mohamad et al., 1998). To estimate statewide VMT, regression models can also forecast VMT based on explanatory variables such as per capita income, gross state income, gross domestic product, and vehicle registrations (Agbelie et al., 2010; Varma et al., 1992; Sinha et al., 2005), which may influence the magnitude of VMT. These models enhance transportation planning for both county highway departments and transportation agencies, as VMT can be predicted for a given highway segment or highway classification (Castro-Neto et al., 2009; Eom et al., 2006; Mohamad et al., 1998).

Forecasting techniques can be implemented using trend-growth factors or regressions using time-series data (INDOT, 2014; Liu and Kaiser, 2006). Growth factors, which are used to adjust from one year's traffic volume to another, are popular with SHAs due to their simplicity and ease of application. Empirical Bayesian forecasting techniques have been examined for AADT-data forecasting (Davis and Guan, 1996; Al-Masaeid and Al-Omoush, 2014; Zheng et al., 2006). By relating existing known AADT data with updated data when available, Bayesian techniques may have potential for more accurately estimating future traffic volumes, which would be helpful for transportation planning applications that rely on these estimates of traffic conditions in a given jurisdiction.

Time series techniques are similar in that quality input data are required. Regressing AADT to forecast future traffic volumes has been widely researched (Lowry and Dixon, 2012; Zhao and Chung, 2001). Spatial interpolation of AADT data has potential for improving the accuracy of AADT predictions (Eom et al., 2006). These approaches may be more suitable for project or regional-level applications, but not for statewide projections.

Socioeconomic models based on national travel surveys, such as the NHTS, or other reliable traveler information include a variety of inputs such as explanatory variables of vehicle registrations, households, population density, and gasoline and diesel prices. California's state transportation agency, Caltrans, uses a "motor vehicle stock, travel, and fuel forecast" model with socioeconomic variables including vehicle registration, fuel consumption, population, and income to forecast VMT (Jones, 1998). This macroeconomic method is considered a more robust approach compared to the traditional statewide travel demand models used as inputs for environmental assessments and economic development planning.

A specific model developed to estimate Indiana VMT was based on NHTS data including household size, household income, and number of vehicles to determine the personal component of VMT, applicable for vehicle classes 1 to 3 (Fricker and Kumapley, 2002). For the commercial component of statewide VMT, the researchers used governmental fuel sales records to generate a rough estimate of VMT. The personal and commercial components were totaled to represent Indiana's statewide VMT.

For FHWA reporting, relating fuel consumption to the amount of statewide travel is thought to be the earliest method of determining VMT dating back to the 1950s, when the interstate highways were constructed. Estimating VMT can be obtained indirectly from fuel sales records. To estimate total VMT, the total fuel revenue for the study area, fleet fuel efficiency, and current fuel tax rates are used (Kumapley and Fricker, 1996). With the fuel-revenue method, it is relatively easy to generate an aggregate estimate of the statewide VMT, but is limited by the lack of estimation by functional class. A New York DOT study (Erlbaum, 1989) proposed that VMT could be calculated using a county's average share of the state touring route and a proportion of car registrations. Gasoline sales, along with car registration produced aggregate VMT estimates. However, validating using VMT calculated from a traffic-based source was not possible. The estimates produced from fuel-based methods are expected to be an underestimate of actual conditions because many vehicles, such as class 5 trucks or government vehicles, can be exempt from certain taxes; thus, producing a low fuel gallonage used for VMT estimation. The reliability of fuel-inputs including the traffic stream distribution and fuel efficiencies are also concerns (Vasudevan and Nambisan, 2013), with fleet fuel efficiencies increasing due to governmental mandates and automotive improvements, which may not necessarily correspond to lower VMT. Outside factors such as weather conditions, road surface, and vehicle age, can affect the fuel efficiency obtained, compared to the manufacturer's estimates. This may affect VMT estimates, since the basis is on fuel consumption and fleet efficiency.

Odometer readings have been proposed as a means to estimate VMT; however, this is not considered a reliable or supplementary method to traffic-based VMT methods for statewide estimation. Due to a long-list of possible errors, including rollovers, tampering, faulty odometer calibration, and reporting errors, the existing body of research has shied away from VMT estimation using odometer readings (Kumapley and Fricker, 1994; Vadlamani, 2005). Obtaining the data, for one, is a major limitation. Many states do not require a self-reported odometer mileage on annual vehicle registration renewal forms sent to motor vehicles agencies. There are also discrepancies with self-reported mileage data, with an Energy Information Administration (EIA) report finding that a single self-reported mileage was higher than the actual mileage traveled, compared to those whom received two forms to record annual mileage (Schipper and Moorhead, 2000).

2.3.2 Methods of Traffic-Based Estimation

States tasked with supplying annual traffic counts for the HPMS, and internal applications, often use a combination of temporary and long-term ATRs, with weigh-in-motion (WIM) sensors located at select sites.

The Indiana road network that is non-state owned, the local road network, consists of around 84,000 miles of county roads and city and town streets, estimated based on annual operational reports and INDOT road inventory (Local Technical Assistance Program, 2009). With this extensive mileage of local roads in Indiana, it is not efficient or feasible to install traffic counting devices for all road segments of the network.

Instead, sampling procedures are often used to represent local roads traffic volumes and thus VMT. For relatively homogenous road networks, such as paved county roads or gravel county roads, simple random sampling may be suitable for traffic volume estimation. However, many local road networks are heterogeneous, and an alternative sampling approach is stratified random sampling, which uses a limited sample of highway sections within a specific functional class. This approach is more accurate if the average sample AADT represents the greater population of traffic counts (Mohamad, 1997; Mohamad et al., 1998).

State routes, such as Interstates or US Highways, are also more suited to stratified random sampling because of the wide range of observed traffic volumes for these highway categories. The traffic count sample at the statewide level was stratified by per capita income, highway mileage, and population density in past studies on VMT estimation (Fricker and Saha, 1987; Mohamad, 1997).

The link-level sampling approach institutionalized by the FHWA and EPA is the HPMS, which is a national repository of traffic, pavement, and performance data, deemed to be representative of the nation’s highway system. Full documentation of the HPMS sampling procedures and traffic data processing can be found in the latest *Traffic Monitoring Guide* (Office of Highway Policy Information (OHPI), 2014b).

To generate a universe-wide (statewide) daily VMT estimate, $\mathrm{DVMT_{total}}$, Equation 2.1 is used, where i represents the volume group, j represents the functional class, and k represents the sample section. The HPMS submittal software provides expansion factors, EF_{ij}, to represent universe-wide VMT that are frequently evaluated by FHWA staff for accuracy and representation (Office of Highway Policy Information (OHPI), 2014c).

$$DVMT_{total} = \sum_{i}\sum_{j}\sum_{k} DVMT_{ijk} \text{ x } EF_{ij} \quad \ldots\ldots\ldots..(2.1)$$

Researchers have modeled traffic data with GIS and software such as TransCAD, to connect roadside attributes such as speed limits, high occupancy vehicles (HOV) lanes, and land-area usage, to estimate the AADT distribution, and therefore, VMT distribution, because each count is connected to the road network. The regional VMT can be obtained from this approach, which may be applicable for air quality studies and transportation planning applications (Bhat and Nair, 2000; Vadlamani, 2005).

Although there are many strengths with link-segment-level (link-level) traffic methods, a limitation is the tendency to underrepresent travel on local and county roads. Building the road networks or inventory, with database managers or Excel, for example, is often impractical for roads that are not higher functional classes such as Interstates and principal arterials. Traffic counting for local roads are typically the responsibilities of county engineers, MPOs or RPOs, or city planning authorities. It is challenging to obtain consistent data to represent local roads in different regions of the state. Table 2.1 compares the advantages and disadvantages of a link-level method from a sample, such as the well-known HPMS for estimating statewide VMT from a sample of representative highway segments and their respective traffic counts.

Table 2.1 Comparison of link-level methods based on sampling procedures

Advantages	Disadvantages
Based on actual traffic counts	Time-consuming traffic data collection
Provides by functional classes	Minimal traffic data outside of the SHS
Not reliant on self-reported travel surveys	Higher costs from training and field staff
System familarity	Expansion factors may be erroneous
Clearly defined processes	Accounting for changing travel patterns
Annual reporting to federal government	Bias from random sampling
Recommended by the EPA for air pollution assessments	
Interstates and the SHS are well-represented	

Users involved in the process, such as MPOs/RPOs, city governments, and field staff are often familiar with the data collection process and the process is well-documented (Office of Highway Policy Information (OHPI), 2014a; c). However, the quality of the sampling design is crucial for the end-quality of the VMT estimate. Non-homogenous road classifications can lead to incorrect estimates if the roads do not have the same number of lanes or volume characteristics when expanded to the population (Fricker and Kumapley, 2002; Vadlamani, 2005).

Theoretically, travel demand models (TDM) can be used to estimate statewide VMT. However, the road network and traffic counts data would have to be extensive for all regions of the state and fully cover all local roads not-owned by the state transportation agencies. Thus, TDM is often used at the project level to simulate travel behavior and also to carry out scenario-based analysis (Atkins Company, 2013; Cambridge Systematics, 2012). At the project level, traffic, socioeconomic, and land-use data can be used to forecast traffic volumes corresponding to the model’s road network representing the state’s primary highway systems. A gravity model is a key component of the four-step process incorporated into TDMs, which consists of trip generation, trip distribution, mode choice, and trip assignment (Wang, 2012; Zhong and Hanson, 2009), as illustrated in Figure 2.6. Mode choice commonly consists of automatic, transit, and non-motorized, depending on the available options for the geographic area of interest. Trip assignment involves origin-destination trip tables to “route” trips to the road network. Traffic flows by time of day and often vehicle type, are used to estimate the daily VMT for the study area.

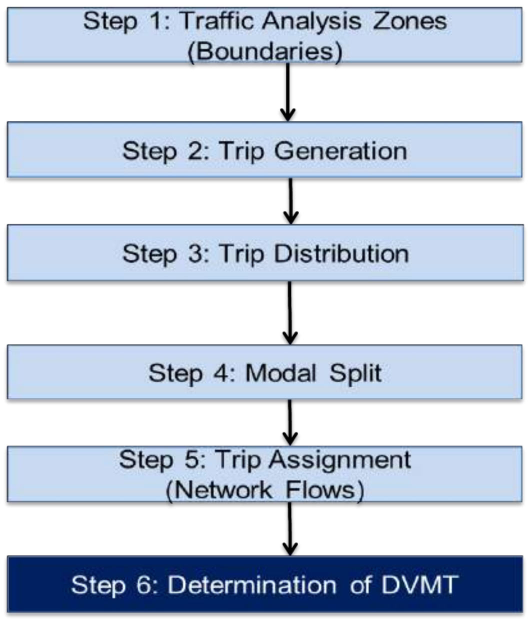


Figure 2.6 Typical steps of travel demand model for VMT estimation

2.4 Highway Classification

The classification schemes used for the highway vehicles and roads is the same as the standard FHWA systems adopted by all states. The systems adopted in this study are described in this section.

2.4.1 Vehicle Classification

Traffic data for this study are classified based on the FHWA 13 vehicle classes shown in Table 2.2, referenced from requirements in the *2013 Traffic Monitoring Guide* (Office of

Highway Policy Information (OHPI), 2014b). For a visual depiction of these types of vehicles, refer to Figure 2.7, adapted from the FHWA vehicle classification publications (Office of Highway Policy Information (OHPI), 2011). The distinction between trucks is based on the number of axles and weights.

Classes 1-3 are personal vehicles, Class 4 is buses, Classes 5 to 7 are commercial single-unit trucks, and Classes 8 to 13 are commercial combination trucks. For purposes of this study, the commercial component of VMT is defined as classes 4-13 and personal-component of VMT is defined as classes 1-3.

Table 2.2 FHWA vehicle classification system (OHPI, 2014b)

Vehicle Class	Vehicle Description
1	Motorcycles
2	Passenger cars
3	4-tire, single-unit vehicles (pickup trucks)
4	Buses
5	2-axle, 6-tire, single unit trucks
6	3-axle, single-unit trucks
7	4-axle or more, single-unit trucks
8	4-axle or less, single trailer trucks
9	5-axle, tractor semitrailer trucks
10	6-axle or more, single trailer trucks
11	5-axle or less, multi-trailer trucks
12	6-axle, multi-trailer trucks
13	7-axle or more, multi-trailer trucks

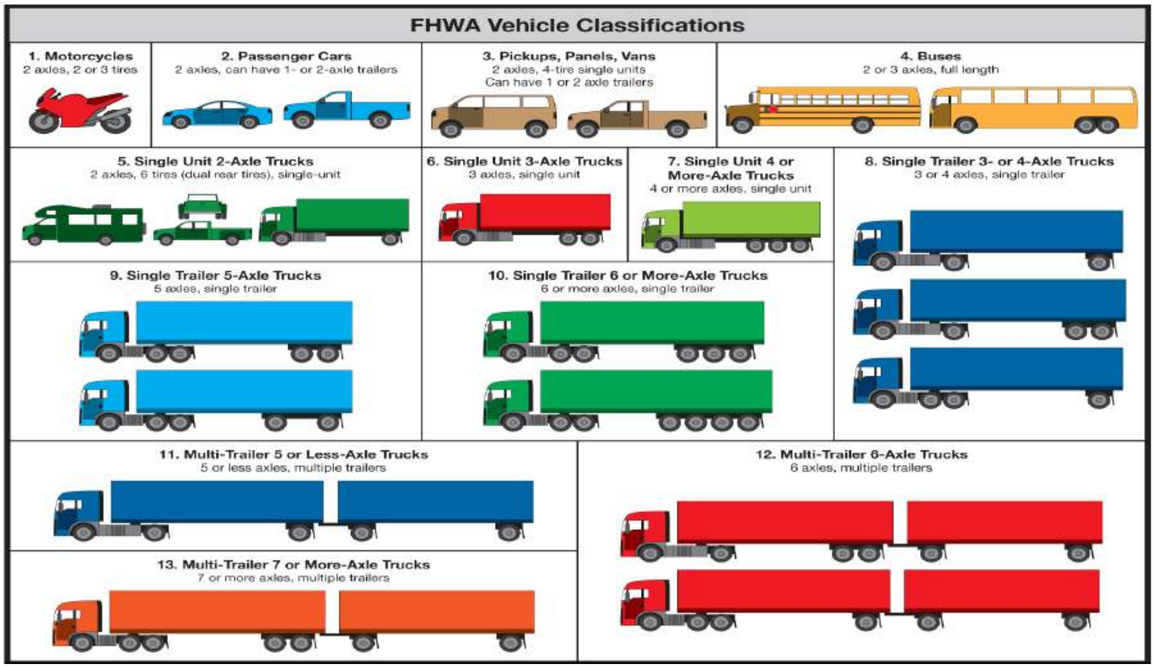


Figure 2.7 Visual depiction of FHWA vehicle classifications (OHPI, 2011)

2.4.2 Functional Classification

Due to changes in the designation of urban area boundaries (UAB), and to better align with the priorities of the U.S. Census (USC), the highway functional classification system has changed after 2008. There is no longer a separate rural and urban category for each division of road, such as Urban Interstates and Rural Interstates. As shown in Table 2.4, the updated FHWA functional classes are used for this study. Migration from the previous twelve functional classes shown in Table 2.3 to the current seven functional classes will be required (Office of Highway Policy Information (OHPI), 2014b).

Table 2.3 Previous FHWA functional classification system (FHWA, 2013)

Category	*Division*	*Subcategory*	*Code*
Rural	Principal Arterials	Interstate	1
Rural	Principal Arterials	Other Princpal Arterials	2
Rural	Minor Arterials	N/A	6
Rural	Collector	Major Collector	7
Rural	Collector	Minor Collector	8
Rural	Local	N/A	9
Urban	Principal Arterials	Interstate	11
Urban	Principal Arterials	Other Freeways & Expwys	12
Urban	Principal Arterials	Other Princpal Arterials	14
Urban	Minor Arterials	N/A	16
Urban	Collector	N/A	17
Urban	Local	N/A	19

Table 2.4 Current FHWA functional classification system (FHWA, 2013)

Category	*Division*	*Subcategory*	*Code*
	Principal Arterials	Interstate	1
	Principal Arterials	Other Freeways & Expressways	2
	Principal Arterials	Other	3
	Arterials	Minor Arterial	4
	Collector	Major Collector	5
	Collector	Minor Collector	6
	Local	N/A	7

2.5 Chapter Summary

This chapter presented a review of the past literature on the two main approaches for VMT estimation, traffic and non-traffic based. VMT estimation methods within each approach were discussed, and their associated merits and limitations were identified. Matrices were used to summarize the data inputs, the characteristics of the VMT estimation methods, and the level of coverage provided for the end-user of the VMT information. The problems identified within VMT estimation with respect to traffic and non-traffic based methods were also discussed.

2.5.1 Limitations of Traffic-Based Methods

The staff training and expense for processing traffic data is one of the problems with traffic-based methods, such as using coverage count programs for statewide VMT estimation. The outside traffic-count contractors must be familiar with the agency's traffic count program. The database must be updated with new links as roads are constructed or decommissioned. Also, sampling bias could be introduced toward important sites, such as those locations in urban areas or near commercial corridors.

As discussed, local roads may not be fully represented in VMT estimation because of the lack of available traffic counts and complete inventory definition. For estimating the statewide contribution of local road VMT, a sample of traffic counts is often used to represent the entire population. Local roads often rely on a sample of traffic counts to represent the entire population.

Also, any changes in land-use and economic patterns may not be accounted for. These factors affect the applicability of the expansion factors used to represent county-wide VMT. If travel demand models are used for VMT estimation, the local road network may have limited representation, which is often the case.

2.5.2 Limitations of Non Traffic-Based Methods

Non-traffic methods rely on inputs that are dynamic and often require a wide-range of data from different agencies. Compiling this data is often cumbersome and may not be complete for each analysis year of VMT estimation. Fuel efficiency, or the mileage per gallon that a vehicle uses, in particular, is an input which is difficult to estimate but has a critical role in the fuel-based method of VMT estimation.

Data from nationally-conducted travel surveys is often not released annually, and thus may contain outdated data. Also, household surveys cannot typically account for commercial activity, and thus their applicability for statewide estimation is limited for a state such as Indiana with significant trucking activity. Fluctuations in economic conditions can also affect VMT estimates, leading to possible misrepresentation of actual VMT. This is particularly worrisome in socioeconomic regression models, where economic indicators are key inputs in the models. Specification errors with the included variables could also impact the results.

Finally, the non-traffic methods for VMT estimation often cannot directly estimate VMT by functional or vehicle class, with an exception of the fuel-based method capable of estimating VMT by vehicle classes. The non-traffic methods typically yield aggregate VMT estimates (statewide totals) derived from non-traffic inputs such as fuel sales, regression models, socioeconomic, and demographic data. These methods are more suitable for a network level assessment of statewide VMT.

Project level applications are not possible without traffic data for a highway segment. For example, if the user desires to obtain the VMT by route at either a project or corridor level, such as a section of I-65 or the entire length of I-465, then the non-traffic methods are not appropriate. This is a limiting factor for agencies tasked with gauging the changing personal and commercial VMT in different regions of the state. Similarly, if the distribution of vehicle classes for a specific route is needed, then a link-level method may be most appropriate.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

To develop a framework for the estimation of statewide VMT, the ideal approach would be to represent the VMT for every segment of the state's centerline road network, which uses actual on-the-ground traffic counts and thus is based on the vehicle movements that comprise VMT. However, with Indiana's 90,000+ miles road network, this approach is limited by the costs and resources required for installing and managing ATRs, WIM stations, and coverage counts, as well as the costs of processing and managing the collected data. For local roads, which are outside the state highway system and also dominate the state's road network, this is impractical.

This study developed a repository of traffic counts from INDOT, MPOs, RPOs, and other organizations. A robust, comprehensive, and adaptable database that covers all the mileage of public roadways was established. The state routes are defined as interstates, US roads, and state roads and are under the jurisdiction of the state government. Local routes are defined as city streets and county roads are under the jurisdiction of municipalities and counties. For state routes, all state owned highway segments' traffic counts are used for the VMT estimation; for local routes, a sample of non-state owned road segments is used.

Also, this study provides analysis to minimize the inconsistencies present from the different VMT estimation methods used at INDOT and other organizations, such as MPOs, legislatures, and state departments. In this chapter, methods such as those based on fuel, vehicle registration, licensed drivers, and trend analysis (discussed in Chapters 1 and 2) are analyzed to provide a range of percent deviations from the ground-truth control or the statewide VMT estimated by the selected method. This increases the reliability and consistency of different VMT estimates and provides an implementable framework that compares the different estimates and provides suitable calibration factors.

3.1.1 Desired Qualities of Framework

To develop this described framework, certain important characteristics were desired. First, available and current traffic counts from both short-term and long-term count stations are required. Second, extensive coverage of all routes, both on and off the SHS, should be possible. Third, the end-user should be provided with coverage for the project, regional, and statewide levels, as well as an easily updatable database to account for a dynamic road network inventory. Fourth, the framework should allow for aggregation by vehicle classification, functional classification or highway category, and geographical scope. These aggregations are essential for agency processes such as highway cost allocation, revenue forecasting, and other applications discussed in Chapter 1. Finally, the system must be easily accessible to INDOT personnel with readily-available software, such as a spreadsheet or GIS platform.

3.1.2 Survey of VMT-Data Stakeholders

To gauge the challenges faced and the level of aggregation required by the users and producers of VMT within INDOT's planning, economics, and traffic safety divisions, an electronic survey was conducted of those divisions. The survey was administered using Purdue Qualtrics, an online tool. The questions were designed to be addressed easily and were in both multiple-selection and open-ended formats. The responses yielded insight about the data needs for a proposed platform and identified the challenges that VMT-data stakeholders face with existing VMT estimation methodologies and procedures.

3.1.3 Selection of Estimation Methodology

As evident from the literature review, the non-traffic based approaches tend to be prone to discrepancies, require excessive resources for data compilation and estimation, and often lack full coverage regarding both personal and commercial travel. The existing traffic-based methods, as currently applied in practice, are woefully inadequate for applicability to local routes. It is important that city streets and county roads are better represented in the coverage count programs.

From the literature review's synthesis of findings and desired framework qualities, a segment of the project level approach (which will be called the "link-level method" for the remainder of this thesis) was selected as the ground-truth VMT estimation method.

This link-level method uses actual on-the-ground traffic counts obtained from both short-term coverage stations and long-term permanent stations to represent statewide travel on Indiana's highways. The link-level method is capable of providing VMT estimates for a specific range of locations, such as between a range of mileposts on a route, as well as aggregations of all routes to produce an area-wide VMT estimation. Importantly, VMT estimation by vehicle classes and functional classes is fully possible and robust using this method. Finally, the link-level method is implemented with Excel or a GIS platform, providing powerful analytical capabilities and an updatable inventory. As more recent traffic data become available, this method allows the records to be updated. This method enhances consistency, reliability, and accuracy for both users and producers of VMT information.

3.2 Framework for Non-Traffic Methods of VMT Estimation

To investigate the discrepancies obtained from varying VMT estimation approaches, comprehensive Indiana-specific data were collected from a variety of sources to estimate statewide VMT. These estimates were then compared to the benchmark, that is, the VMT estimated using the link-level method, in order to gauge the extent of under or over-estimation from each of these methods.

The theoretical background behind the suitability of these methods for statewide estimation is provided in Chapter 2. Also provided are an overview of the requested inputs and outputs, not only to explain the estimation procedures applied, but also to provide insight into the suitability of each approach for the end use in question.

3.2.1 Based on Fuel Revenue and Fleet Efficiency

The fuel-based approach for estimating statewide VMT for revenue forecasting and long-term planning is one of the most common approaches for non-traffic based VMT estimation.

As shown in Figure 3.1, the three main inputs for the fuel-based method include fuel tax rates, fuel revenue, and fleet fuel efficiencies; and the fleet fuel efficiencies are affected by a variety of inputs. The fuel tax rates and fuel revenue are required for estimating the gallonage of fuel used. Fuel tax rates are known and infrequently change. Past fuel revenues are reported in annual Department of Revenue (DOR) reports (IDOR, 2014). Other inputs affecting fleet fuel efficiencies (Office of Highway Policy Information (OHPI), 2014d) include the vehicle class distribution, the percent of vehicles running on gasoline and diesel, and the vehicle fleet age.

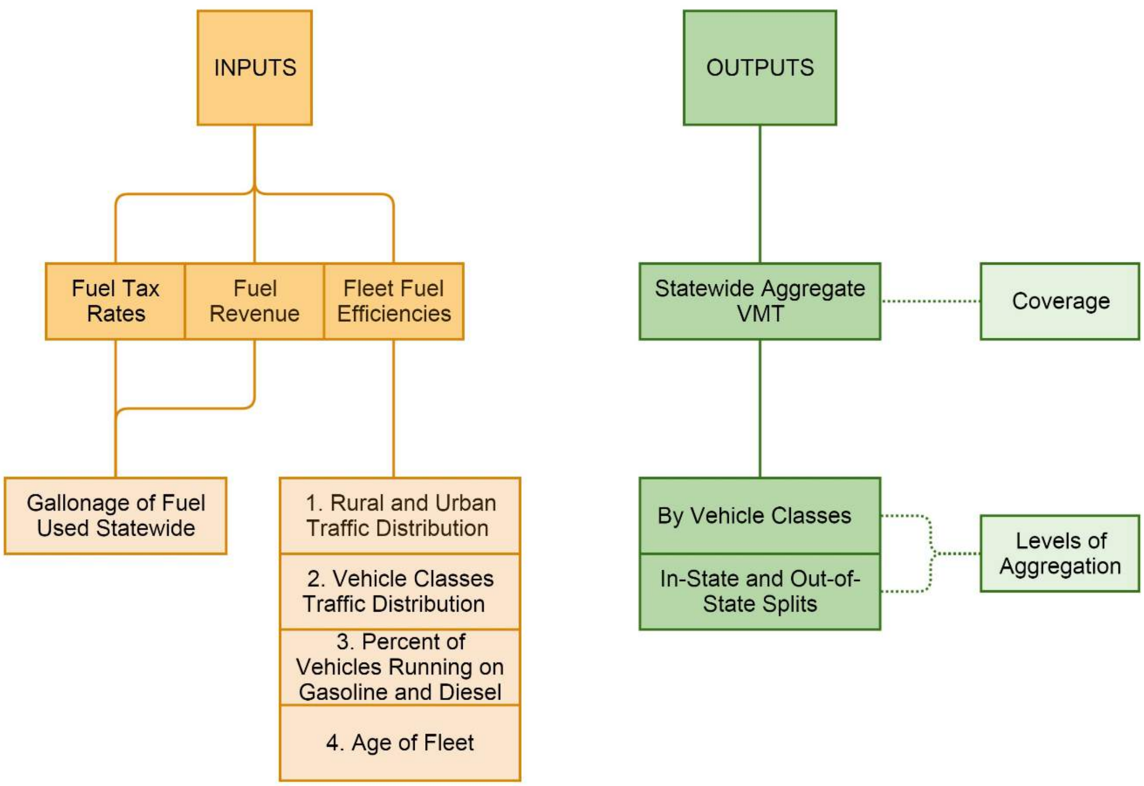


Figure 3.1 Flowchart for statewide VMT estimation involving fuel-related data

Typically, this method yields a statewide aggregate VMT because fuel revenue and fuel gallonage are reported on an annual basis. The coverage provided is typically statewide aggregate VMT, since fuel revenues and fuel gallonage are typically reported on an annual basis. The levels of aggregation include vehicle classes and the in-state vs. out-of-state split.

The calculation for statewide annual VMT is given as Equation 3.1; i representing the fuel type (gasoline or diesel), and j representing the individual vehicle class, with units of fleet fuel efficiency given in miles/gallon, fuel revenue in \$, and fuel tax rate in \$/gallon.

$$\text{Annual VMT} = \sum\left(\text{Fleet Fuel Efficiency}_{\text{ij}}\right)\left(\frac{\text{Annual Fuel Revenue}_{\text{ij}}}{\text{Fuel Tax Rate}_{\text{ij}}}\right)\ldots\ldots\ldots\ldots(3.1)$$

Different assumptions affect the distribution of the estimated fuel consumption across the vehicle classes. For example, aggregate approaches often assume that non-commercial vehicles (classes 1 to 3) are powered solely by gasoline. According to the Energy Information Administration (EIA, 2014), approximately 98% of the existing vehicles in this group use gasoline. However, the same data show that a significant number of vehicles in this group use diesel; and also that several commercial vehicles, such as Class 5 trucks, use gasoline.

In a disaggregate approach, for each vehicle class, estimates of the percentage of vehicles by each fuel type are used to distribute the fuel consumption to each vehicle class, and then multiplied by FFE to estimate VMT. This, in theory, is expected to be more accurate; however, the quality of the end product is as good as the integrity of the input data.

3.2.2 VMT Estimation Based on Trend Analysis and Growth Factors

The analysis of historical data to predict future conditions has often been used as a benchmark for comparing VMT estimates. Estimation inputs include previously-reported historical VMT data for a continuous and consistent time span. FHWA has kept consistent records for over 20 years in the form of the HPMS statewide figures reported in *Highway Statistics*. Another source is state transportation agencies such as INDOT that keep records of their VMT estimates by county and functional system. An aggregate statewide value for future years is predicted using time-series forecasting with varying functional forms.

It is intuitively expected that as the analysis period increases from the last data point, the reliability reduces because of an increase in errors due to external factors such as economic downtown, changing workforce, and development of cost-effective alternatives to automobiles. For example, if an analyst seeks to predict the VMT of the year 2030 using 1990 to 2008 data, then this estimate may not be influenced by the major economic recession that occurred in 2009.

Growth factors are developed from analyzing a present and past point of the available time-series data. These growth factors can be applied to a present year AADT or VMT value to obtain a future value. The equations used to calculate an annual growth factor and predict a future value are presented as Equation 3.2 and Equation 3.3, respectively, where N represents the number of years of difference between the start and end of the time period, y represents the future year for estimation, x represents the most recent year, and i represents the average annual growth rate.

$$\text{Annual Growth Rate, i} = \frac{\frac{\text{AADT}_{\text{present}} - \text{AADT}_{\text{past}}}{\text{AADT}_{\text{past}}}}{(\text{N})} \ldots\ldots\ldots\ldots\ldots\ldots.(3.2)$$

$$\text{Future AADT, AADT}_{\text{y}} = \text{AADT}_{\text{x}}(1+\text{i})^{\text{N}} \ldots\ldots\ldots\ldots.\ldots(3.3)$$

A variety of functional forms can be investigated and the goodness of fit can be gauged by the standard coefficient of error, R^2. A higher R^2 indicates a superior fit;

however, the results should be validated using data points excluded from the modeling dataset. In this study, the linear, exponential, polynomial, S-curve, and logarithmic functional forms were investigated for forecasting VMT.

3.2.3 VMT Estimation Based on Socioeconomic Regression

In this method, regression models developed for forecasting VMT inputs for highway revenue are applied. The regression models specific to Indiana from a JTRP study (Agbelie et al., 2010) are used in this study. As shown in Figure 3.2, the outputs of the regression models provide statewide coverage with aggregation by vehicle group. Inputs include the Indiana per capita income (PCI), U.S. gross domestic product (GDP), and the Indiana driving age population (DROP).

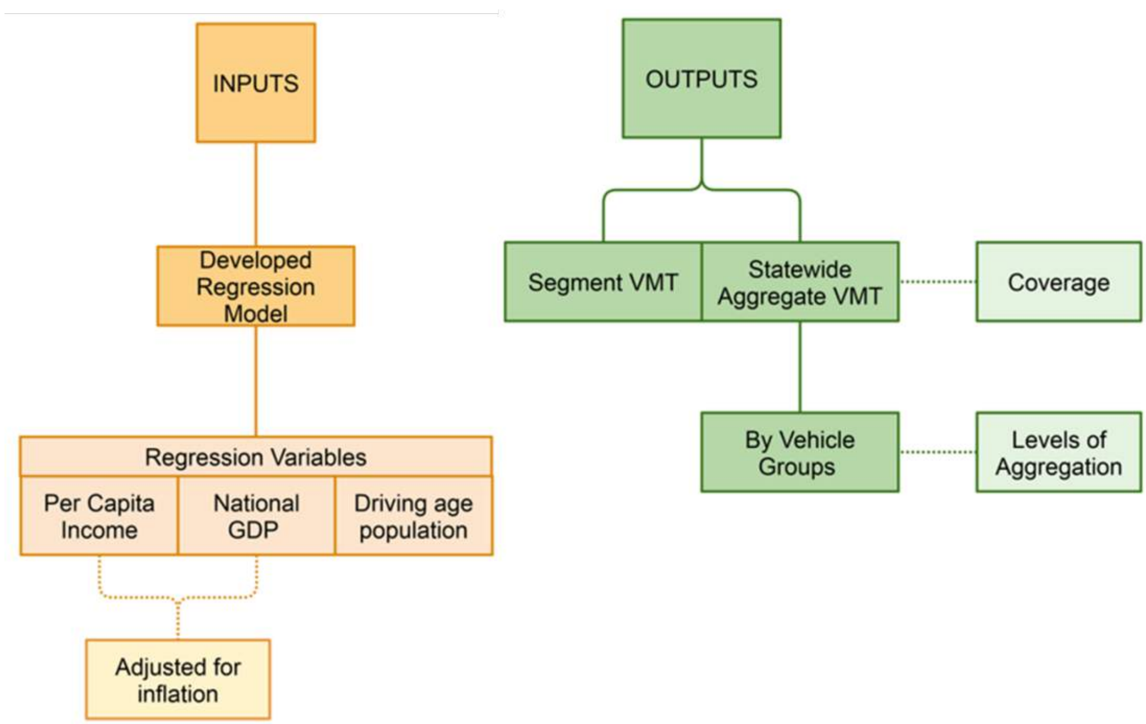


Figure 3.2 Flowchart for VMT estimation from socioeconomic regression model

The regression models for the statewide VMT by vehicle class are presented by Equation 3.4 to Equation 3.9. Indiana's per capita income (PCI) is significant in the most models and greatly affects the VMT. US GDP is significant only in the VMT estimation model for heavy commercial trucks.

$$\text{Motorcycle VMT} = -1331.51 + 0.000368 * (\text{DROP}) \ldots\ldots (3.4)$$

$$\text{Automobile VMT} = 35505 + 0.446 * (\text{PCI}) \ldots\ldots (3.5)$$

$$\text{Light} - \text{Duty Truck VMT} = -652652 + 64036 * \text{LN}(\text{PCI}) \ldots\ldots (3.6)$$

$$\text{Bus VMT} = 9.27 - 0.000106 * (\text{PCI}) \ldots\ldots (3.7)$$

$$\text{Single} - \text{Unit Truck VMT} = 1866.02 + 0.0164 * (\text{PCI}) \ldots\ldots (3.8)$$

$$\text{Class } 9 - 13 \text{ Truck VMT} = 4628 + 0.166 * (\text{USGDP}) \ldots\ldots (3.9)$$

3.2.4 VMT Estimation Based on Vehicle Registrations

With a known amount of vehicle registrations reported to the Bureau of Motor Vehicles (BMV), these records are used with an estimate of average annual travel per vehicle to estimate aggregate statewide VMT. Exempt vehicles that do not register with the BMV may cause this method to underrepresent VMT. It is assumed that in-state travel equals out-of-state travel. For example, the FHWA *Highway Statistics* reports average travel per automobile. This is assumed to balance the share of out-of-state vehicles traveling in-state. Equation 3.10 presents the calculation of statewide VMT, where *i* and AAVMT represent the vehicle class and the average annual VMT.

$$\text{Statewide VMT} = \sum_{j} \sum_{i} (\text{AAVMT}_i) \text{x} (\text{Number of registriations}_i) \ldots \ldots \ldots (3.10)$$

Different vehicle classes have varying amount of travel; automobiles historically travel around 12,000 miles annually, compared to commercial buses with around 30,000 miles annually. Vehicle registrations at the disaggregate level are provided by gross weight (GW) categories, with trucks starting at 10,000 lbs up to 66,000+ lbs.

3.2.5 Based on Licensed Drivers and Demographics

Travel surveys, such as the FHWA-sponsored National Household Travel Survey (NHTS) (FHWA, 2009) are conducted periodically to gauge travel behavior and identify trends. Using demographic, licensed drivers, and travel variables, statewide aggregate VMT is estimated. The framework is shown in Figure 3.3.

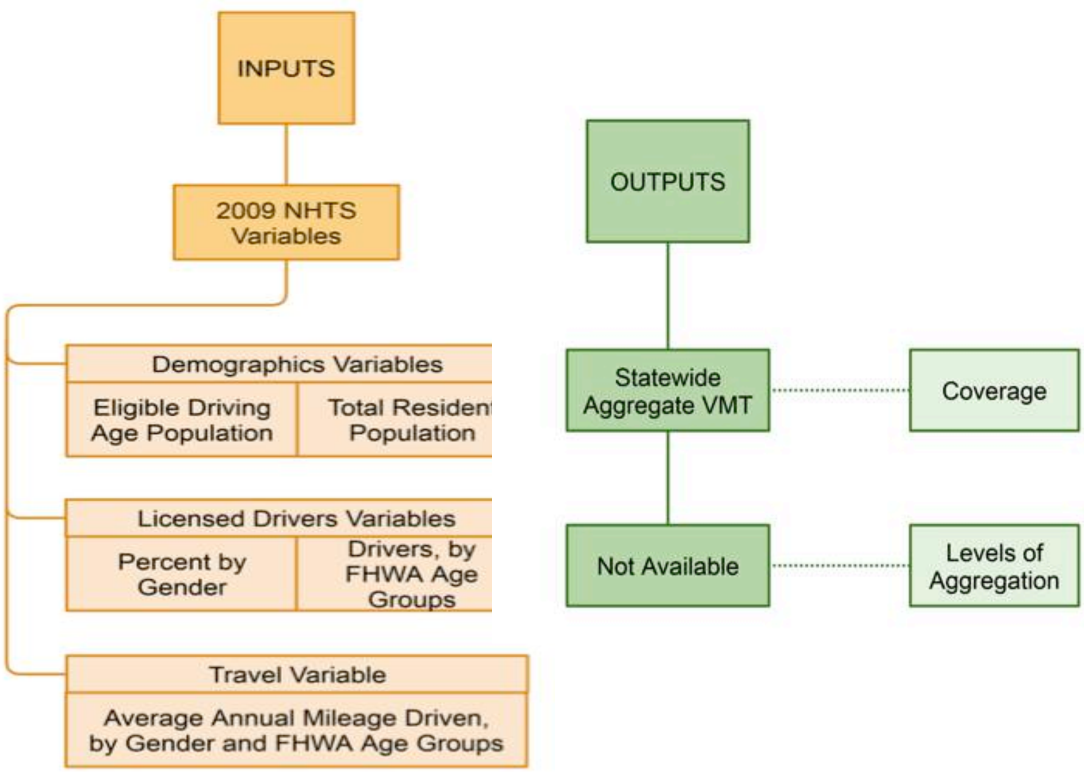


Figure 3.3 Flowchart for VMT estimation using licensed driver surveys

The average annual mileage driver by gender and FHWA age group is expanded to the population of drivers. For example, the population of licensed male drivers ages 16-19 and the average travel per driver yields a statewide VMT estimate for this age group. The same process is repeated for all age groups, with varying annual mileage per each age group.

A sample of drivers from Indiana and surrounding states (Wisconsin, Iowa, Ohio, and Kentucky) is analyzed. These four states were selected based on the similarity in travel characteristics to Indiana, and were used in a similar study to increase the reliability of the sample for estimating statewide VMT from demographic, licensed driver, and travel variables (Kumapley and Fricker, 1994). The samples have varying average annual mileage per driver group, complied from the 2009 edition of the NHTS.

3.2.6 VMT Estimation Based on Socioeconomic Travel Surveys

The online analysis tools of the most recent NHTS edition also allow for quick estimation of VMT using socioeconomic and household characteristics. As shown in Figure 3.4, an example flowchart for statewide VMT estimation from the 2009 NHTS is shown, building upon the work of Fricker and Kumapley (2002). The online analysis tools allow for estimation of VMT using Indiana-specific socioeconomic and household characteristics. The number of vehicles by household income and land-type groups, along with an estimate of average annual VMT per vehicle, allow for statewide VMT to be estimate. This VMT figure is only applicable for personal travel (classes 1 to 3).

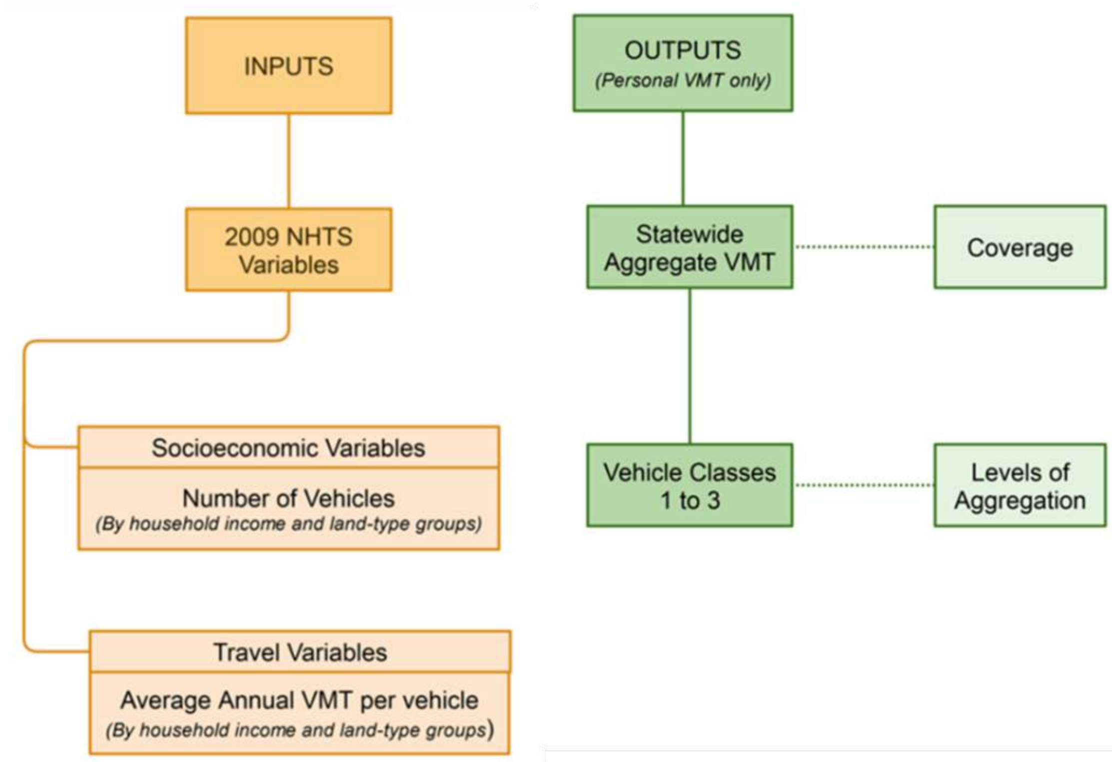


Figure 3.4 Flowchart for VMT estimation from socioeconomic travel surveys

The household VMT is calculated as the summation of the VMT of all households in Indiana, expanded from the sample to represent the population. The variable "bestmile" represents an estimate of annualized mileage per vehicle, which is corrected from the raw data to better represent actual travel. The model requires the population within each land-area type cluster for statewide VMT estimation. For example, the estimated number of household within the three land-types of rural, light-urban (suburban), and urban, is given by the online analysis tools based on the household sizes in the 2000 US Census.

3.3 Data Collection for Non-Traffic Methods

To estimate Indiana's statewide VMT from the VMT estimation methods outlined, a variety of data sources is required. The acquisition, processing, and analysis of the data has degrees of ease and reliability that vary across the methods. The data collection considerations for the non-link-level methods by the required calculation item, accessibility, and reliability, are summarized in the following section.

3.3.1 Summary of Data Collected

Table 3.1 presents a summary of the attributes of the data collected for the non-traffic methods of VMT estimation. The table presents the types of non-traffic calculation items, data sources, years obtained, the ease of access, and the level of reliability (H represents high, M represents moderate, and L represents low). Low access and reliability, which are least desirable, exemplify the challenges faced in compiling and working with data for the non-traffic methods. The data is extensive, comes from a variety of sources different years, inconsistencies observed, and needs updated for future estimates.

In order to estimate VMT from non-traffic data, each method has degrees of data collection. For example, the fuel-revenue based method of VMT estimation requires the most extensive data collection, with fuel tax revenues, fleet fuel efficiencies, traffic stream distributions, and in-state vs. out-of-state split required. While VMT estimation methods using vehicle registrations and travel surveys were observed to require the least extensive data collection. The data collection and compilation, specific to each VMT estimation method, are discussed in the following sections. Discussion of the inputs for each VMT estimation method and respective data sources are provided.

Table 3.1 Summary of data collected for non-traffic methods

Method	Calculation Item	Source	Years Obtained	Ease/Level of Access	Level of Reliability
Fuel-Revenue	Gas and diesel tax revenues	IN DOR	2009-present	H	H
Fuel-Revenue	Fuel consumed for motor transportation	EIA	2009-2013	H	M
Fuel-Revenue	Gas and diesel tax rates	IN DOR	All	H	H
Fuel-Revenue	Fleet fuel efficiencies	Oak Ridge, FHWA Statistics	2009-2012	M	M
Fuel-Revenue	Vehicles powered by fuel type	EIA	2009-2012	M	M
Fuel-Revenue	Traffic stream distributions	SPR3704, FHWA Statistics	2009-2013	M	H
Fuel-Revenue	In-state and out-of-state splits	SPR3704	N/A	H	H
Fuel-Revenue	Age of vehicle fleet	Unavailable	N/A	L	L
Socioeconomic Reg.	Gross domestic product USA	BEA Regional Data	2009-2013	H	H
Socioeconomic Reg.	Driving age population of IN	FHWA Statistics	All	H	H
Socioeconomic Reg.	Per capita income of IN	BEA Regional Data	2009-2012	H	H
Socioeconomic Reg.	Inflation indices for USA, IN	Bureau of Labor, BEA	All	H	M
Socioeconomic Surveys	Average annual mileage per vehicle	NHTS	2009	M	L
Socioeconomic Surveys	Household vehicles by area type	NHTS	2009	M	L
Licensed Drivers	Number of male and female drivers	FHWA Statistics	All	M	M
Licensed Drivers	Total statewide resident population	U.S. Census, FHWA	All	H	H
Licensed Drivers	Average annual mileage per driver	NHTS	2009	L	M
Vehicle Registrations	Classes 1-3 vehicle registrations	Internal, FHWA Statistics	All	M	H
Vehicle Registrations	Classes 4-13 (trucks) registrations	Internal, FHWA Statistics	All	M	M
Vehicle Registrations	Average annual mileage	Dept. of Energy, FHWA	2015	H	M
Vehicle Registrations	Historical statewide VMT reports	INDOT, FHWA Statistics	All	H	H
Vehicle Registrations	Growth factors	Internal	2009-present	L	M
Link Level (HPMS)	Historical VMT by functional class	FHWA Statistics	All	H	H
Link Level (HPMS)	Data for HPMS road sections	INDOT TCDS, MPOs	2009-present	H	H

3.3.2 Data for Fuel Revenue and Fleet Efficiency

Data on gasoline and diesel tax revenues, fuel consumed for motor transportation, gasoline and diesel tax rates, fleet fuel efficiencies, distribution of vehicles powered by fuel type, traffic stream distributions, and in-state vs. out-of-state split, were compiled for estimating VMT. All fuel-based inputs had a high level of access, except the average vehicle fleet age, which was unavailable for this study.

Fleet fuel efficiencies by vehicle classes were compiled from the FHWA *Highway Statistics* VM-1 Tables (Office of Highway Policy Information (OHPI), 2014d) and the Oak Ridge Transportation *Energy Data Book* (Davis et al., 2014) referencing many of the FHWA fuel efficiency estimates. These have a significant effect of the end result from the VMT estimation. Table 3.2 shows the fleet fuel efficiencies used in this study, by vehicle classes 1 to 13 for the analysis period of 2009 to 2013.

Table 3.2 Fleet fuel efficiencies (MPG) by FHWA vehicle classes (OHPI, 2014d; Davis et al., 2014)

Vehicle Classes	2009	2010	2011	2012	2013
Class 1	43.20	43.40	43.20	43.50	43.50
Class 2	23.50	23.30	23.50	23.30	23.30
Class 3	17.30	17.20	17.30	17.10	17.10
Class 4	7.20	7.10	7.20	7.20	7.20
Class 5	7.40	7.10	7.40	7.30	7.30
Class 6	7.40	7.10	7.40	7.30	7.30
Class 7	7.40	7.30	7.40	7.30	7.30
Class 8	6.00	7.30	6.00	5.80	5.80
Class 9	6.00	5.90	6.00	5.80	5.80
Class 10	6.00	5.90	6.00	5.80	5.80
Class 11	6.00	5.90	6.00	5.80	5.80
Class 12	6.00	5.90	6.00	5.80	5.80
Class 13	6.00	5.90	6.00	5.80	5.80

Data on the share of vehicles that consume each fuel type is compiled from the Energy Information Administration (EIA) Annual Energy Outlook 2014 Tables (EIA, 2014a). These distributions are shown in Table 3.3, for diesel vehicles, and Table 3.4, for gasoline vehicles.

Class 1, motorcycles, are assumed for estimation as 100% using gasoline and 0% using diesel. Class 2-3, light-duty personal vehicles, uses Table 60, light-duty vehicle miles traveled by technology type. Reported VMT from gasoline internal-combustion engines (ICE) and diesel ICE is used to estimate the percent shares for each analysis year. For example, 2438.9 billion gasoline VMT and 10.4 billion diesel VMT produce shares of 99.6% and 0.43%, respectively. Classes 5-13, freight vehicles, reference Table 68, for freight transportation energy use. Similar percent shares based on VMT are used for freight vehicles, with Classes 9-13 estimated as equal for large trucks.

Table 3.3 Estimation of percentage of vehicles powered by diesel (EIA, 2014a)

Vehicle Classes	2009	2010	2011	2012	2013
Class 1	0.0%	0.0%	0.0%	0.0%	0.0%
Class 2	0.4%	0.4%	0.4%	0.5%	0.5%
Class 3	0.4%	0.4%	0.4%	0.5%	0.5%
Class 4	95.0%	95.0%	95.0%	95.0%	95.0%
Class 5	61.0%	61.0%	61.0%	61.0%	61.0%
Class 6	81.6%	81.6%	82.2%	81.0%	81.0%
Class 7	81.6%	81.6%	82.2%	81.0%	81.0%
Class 8	81.6%	81.6%	82.2%	81.0%	81.0%
Class 9	97.4%	97.4%	97.4%	97.4%	97.4%
Class 10	97.4%	97.4%	97.4%	97.4%	97.4%
Class 11	97.4%	97.4%	97.4%	97.4%	97.4%
Class 12	97.4%	97.4%	97.4%	97.4%	97.4%
Class 13	97.4%	97.4%	97.4%	97.4%	97.4%

Table 3.4 Estimation of percentage of vehicles powered by gasoline (EIA, 2014a)

Vehicle Classes	2009	2010	2011	2012	2013
Class 1	100.0%	100.0%	100.0%	100.0%	100.0%
Class 2	99.6%	99.6%	99.6%	99.5%	99.5%
Class 3	99.6%	99.6%	99.6%	99.5%	99.5%
Class 4	5.0%	5.0%	5.0%	5.0%	5.0%
Class 5	39.0%	39.0%	39.0%	39.0%	39.0%
Class 6	18.4%	18.4%	17.8%	19.0%	19.0%
Class 7	18.4%	18.4%	17.8%	19.0%	19.0%
Class 8	18.4%	18.4%	17.8%	19.0%	19.0%
Class 9	2.6%	2.6%	2.6%	2.6%	2.6%
Class 10	2.6%	2.6%	2.6%	2.6%	2.6%
Class 11	2.6%	2.6%	2.6%	2.6%	2.6%
Class 12	2.6%	2.6%	2.6%	2.6%	2.6%
Class 13	2.6%	2.6%	2.6%	2.6%	2.6%

Historical fuel revenue data for gasoline and diesel were obtained from the Indiana Department of Revenue (DOR) Annual Reports from 2012-2014, along with the current fuel tax rates (IDOR, 2014). Surcharges for motor carriers and commercial shippers are additional revenue, but does not affect fuel consumption. As shown in Table 3.5, based on the current gasoline tax rate of $0.18 per gallon and diesel tax rate of $0.16 per gallon, the gasoline and diesel consumption is estimated.

Table 3.5 Indiana DOR fuel-tax revenue by fuel type (IDOR, 2014)

Year	Gasoline Revenue	Diesel Revenue	Gasoline Gallonage	Diesel Gallonage
2009	$535,851,300	$162,777,400	2.98E+09	1.02E+09
2010	$540,317,900	$167,332,100	3.00E+09	1.05E+09
2011	$543,037,900	$178,161,800	3.02E+09	1.11E+09
2012	$534,704,500	$183,742,000	2.97E+09	1.15E+09
2013	$529,619,800	$169,616,600	2.94E+09	1.06E+09

Table 3.6 EIA estimate of motor fuel consumed (EIA, 2014b)

Year	Gasoline Gallonage (EIA)	Diesel Gallonage (EIA)
2009	2.99E+09	1.20E+09
2010	3.07E+09	1.33E+09
2011	2.93E+09	1.37E+09
2012	2.89E+09	1.34E+09
2013	3.02E+09	1.49E+09

Fuel consumption (based on consumption estimates of fuel used for motor transportation) are provided by the EIA State Energy Data System (SEDS), transoprtation sector energy consumption estimates, for 2009-2013. As shown in Table 3.6, estimates of the total galloange of gasoline and diesel consumed for statewide travel are provided. The orignal values were given in barrels and converted to gallons for consistency with Indiana DOR estimates.

The traffic distribution streams by vehicle classes for the weighted fleet fuel efficiencies are from SPR 3704 data (Volovski et al., 2015) and the FHWA *Highway Statistics*. The rural and urban roads traffic distribution is from Table VM-4 of *Highway Statistics* (Office of Highway Policy Information (OHPI), 2014d) and is used to adjust the original data provided by rural and urban designation.

3.3.3 Data for Trend Analysis and Growth Factors

Time-series data from 1992 to 2008 were modeled to predict annual VMT for 2009 to 2013. Historical VMT by systems and year was easily obtained for 1990 to 2008, allowing for validation of 2009 to 2013, known VMT for comparison (INDOT, 2013). Discussion of the performance for the functional forms analyzed for statewide VMT estimation is provided in Chapter 4.

Growth factors data was derived based on observed trends in the traffic count database developed for this study. Four years of complete segment-level AADT data was used to develop growth factors by functional class. For example, the known present and past VMT, along with the time period between, is used to calculate growth factors. These growth factors were applied to the 2008 VMT to forecast for 2009 to 2013 for comparison of accuracy obtained.

3.3.4 Data for Socioeconomic Regression Model

The socioeconomic regression model had predictive capabilities, but actual economic data for 2009 to 2013 was compiled for comparison. All monetary values were adjusted for inflation and therefore were expressed in constant dollars of Year 2008. Sources for PCI and GDP data were the Bureau of Economic Analysis (BEA) (BEA, 2015). The consumer price index (CPI) from the Bureau of Labor Statistics (BLS) (BLS, 2015) was used to adjust PCI and BEA indices were used to adjust GDP. Table 3.7 presents the numerical model inputs. A PCI lower than the predicted model is observed for 2009 to 2010, obviously from the economic recession. A similar observation was made for GDP. The Indiana driving age population used in the socioeconomic regression model was compiled from the FHWA *Highway Statistics* DL-1C tables (Office of Highway Policy Information (OHPI), 2014d).

Table 3.7 Summary of inputs for the socioeconomic regression model

Year	**Per Capita Income of Indiana**		**GDP of USA**		**Driving Age Population of Indiana**	
	2008$		billions of 2008$		number of drivers	
	Predicted	Actual	Predicted	Actual	Predicted	Actual
2009	$34,947	$30,393	$15,854	$13,143	4,844,014	5,015,383
2010	$35,245	$30,986	$16,091	$13,759	4,883,437	5,061,394
2011	$35,543	$32,811	$16,329	$14,242	4,922,860	5,102,910
2012	$35,841	$34,407	$16,566	$14,866	4,962,283	5,127,883
2013	$36,139	$35,616	$16,804	$14,851	5,001,706	5,164,988
2014	$36,437	$37,003	$17,041	$15,416	5,041,129	5,182,850

3.3.5 Data for Vehicle Registrations

The vehicle registration method relies on two main inputs. The first is the amount of travel per vehicle. This measure is the annual VMT per each vehicle. To obtain this estimate, at least one estimate was obtained for each vehicle group. The statewide VMT was estimated for the low and high range of passenger car mileage because of the significant contribution to the total VMT. Table 3.8 shows a summary of the annual mileage per vehicle group. The sources of the mileage estimates are primarily from the FHWA *Highway Statistics VM-1 Series*, the American Public Transit Association (APTA) (APTA, 2014) and the Alternative Fuels Data Center (AFDC) (AFDC, 2015).

Table 3.8 Summary of annual mileage by vehicle group

Vehicle Registrations: Annual Mileage Estimates					
Vehicle Group	**Estimate (1)**	**Estimate (2)**	**Average Estimate**	**Source of Mileage Estimate(s)**	
Motorcycles	2,423	2,529	2,476	(1) FHWA VM-1 (2013)	(2) FHWA VM-1 (2012)
Passenger Cars	11,262	13,476	13,476	(1) FHWA VM-1 (2012)	(2) FHWA NHTS (2009)
Light-Duty Trucks	11,346	11,712	11,529	(2) FHWA VM-1, 2013	(2) AFDC, Department of
Transit Buses	34,053		34,053	(1) APTA Tables 6, 7 (2014)	
School Buses	12,000		12,000	(1) National School Bus Fuel	
Long-Haul Trucks	66,260	68,155	67,208	(1) FHWA Table VM-1 (2012)	(2) FHWA VM-1 (2013)
Single-Unit Trucks	12,894	13,116	13,005	(1) FHWA Table VM-1 (2012)	(2) FHWA NHTS (2009)

3.3.6 Data for Licensed Drivers and Demographics

Demographic inputs required for calculations, including the number of male and female licensed drivers, total population, and ratios of male and female drivers relative to the total driving age population, were retrieved from the time-series data from the FHWA *Highway Statistics* DL-1C tables (Office of Highway Policy Information (OHPI), 2014d).

Indiana did not provide 2010 demographic data to the FHWA, so trend analysis was used to substitute for unavailable 2010 data. Also, data from 2011 and 2012 seemed erroneous because the reported number of licensed drivers was approximately the same as the total statewide resident population. A similar discrepancy in the reported FHWA data for Indiana has been noted in a past thesis (Kumapley, 1994). For example, reported data shows 3.330 million male drivers and 3.240 million female drivers (totaling 6.570 million), whereas the statewide resident population is 6.516 million and 6.537 million, for 2011 and 2012, respectively. To improve the reliability of the VMT estimate obtained from this method, trend analysis of historical data was used to substitute for the 2011 and 2012 with observed discrepancy.

Kumapley and Fricker (1994) compared samples of drivers from surrounding states of WI, OH, KY, and IA to work with a larger sample size that is statistically similar to IN. While the sample size of the 2009 NHTS has significantly increased, compared to the 1995 NHTS edition, with an IN sample of 2,361 male and 2,306 female drivers, this research compared the efficacy of both datasets. This comparison was facilitated using the built-in SAS script of the Table Designer that allows data to be quickly selected, exported, or processed.

As shown in Table 3.9 and Figure 3.5, the average annual mileage is highest for ages 30 to 49, which is expected because of the higher number of business and personal trips that are often undertaken by this age group. The lowest annual mileage is for ages 75 and over and 19 and under.

Table 3.9 Average annual VMT per licensed driver for the Indiana sample

Age Group	AVMT (Males)	AVMT (Females)	Sample Size (Males)	Sample Size (Females)	Average AVMT (All)
16-19	6,230	6,735	116	93	6,483
20-24	11,138	10,673	71	58	10,905
25-29	17,560	11,795	59	76	14,677
30-34	20,213	12,467	100	110	16,340
35-39	15,959	12,863	126	123	14,411
40-44	19,321	11,649	176	178	15,485
45-49	19,504	12,322	235	243	15,913
50-54	17,324	11,204	272	286	14,264
55-59	14,815	10,433	293	274	12,624
60-64	14,626	9,178	276	259	11,902
65-69	11,868	6,510	231	213	9,189
70-74	10,899	5,886	168	158	8,393
75 and over	8,558	3,820	238	235	6,189

The result from the different sample sizes, for Indiana compared to surrounding states, is similar across all age groups (Figure 3.5). However, there is higher deviation between the two approaches for age groups 45 to 49, 60 to 64, and 65 to 69. This may be due to the sample of drivers which completed the NHTS.

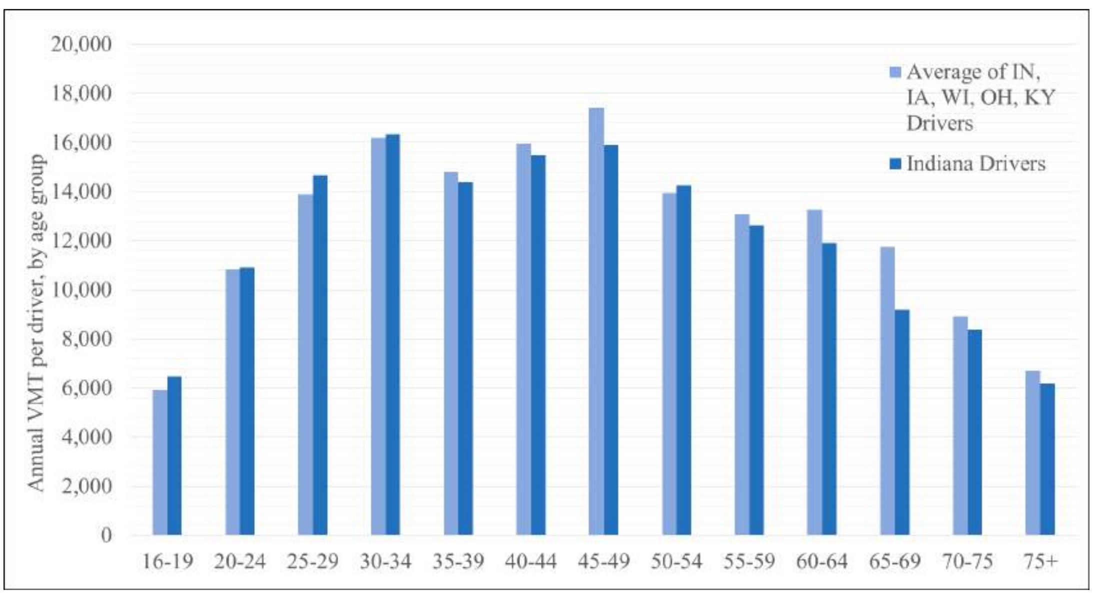


Figure 3.5 Annual VMT per licensed driver by age group

3.3.7 Data for Socioeconomic Travel Surveys

Similar to licensed drivers, the data for VMT estimation based on socioeconomic travel surveys comes from the most current edition of the NHTS (FHWA, 2009). The number of household vehicles, household family income, number of licensed drivers in household, and area type by block groups, are variables used to derive VMT. The land-area type to define urban and rural areas is defined by four groups, consistent with the 2010 U.S. Census (USC): second city, suburban, town and country, and urban. Urban and second city are clustered as dense urban (DU), town and country as rural (RSW), and suburban (S) as Light Urban (LU).

The NHTS estimates the annualized mileage per respondent as the variable “bestmile”, an adjusted derivation of the self-reported mileage that aims to improve reliability. As well as providing an estimate of annual travel, the SAS output provides an estimate of the number of vehicles in Indiana per household location groups. For example, dense urban, light urban, and rural location groups have an estimated number of vehicles per each of the $20K defined income groups. These aggregate estimates of vehicles per area-type are expanded by the average annual travel per vehicle to estimate the personal (classes 1 to 3) component of statewide VMT.

3.4 Framework for Link-Level VMT Estimation

This section provides the development of the methodology framework and vehicle class distributions at the link-level. The link-level for VMT estimation serves as the ground-truth control or benchmark for comparing statewide VMT because it is the most comprehensive estimate that is based on extensive traffic counts across the state. For local routes, the VMT estimation is comprehensively analyzed and discussed due to the historical lack of attention, low accuracy, and inconsistencies associated with this critical component of VMT at this level of jurisdiction. A series of Excel spreadsheets were developed to implement the framework and to serve as the platform for future estimation of VMT by INDOT personnel.

3.4.1 Development of Methodology Framework

As shown in Figure 3.6, state routes are defined for this research as INDOT-owned routes, designated as Interstates, US Roads, and State Roads. This is the first part of the framework for statewide VMT estimation. Subsequently, this is summed with the local route VMT to yield the VMT for the entire Indiana highway system. Local routes are defined as city streets and county roads not owned by the state government, but by counties, municipalities, and local governments. The population of traffic counts and continous segment-by-segment data are available for state routes, and a sample of counts is used as a basis for computation of the local route VMT.

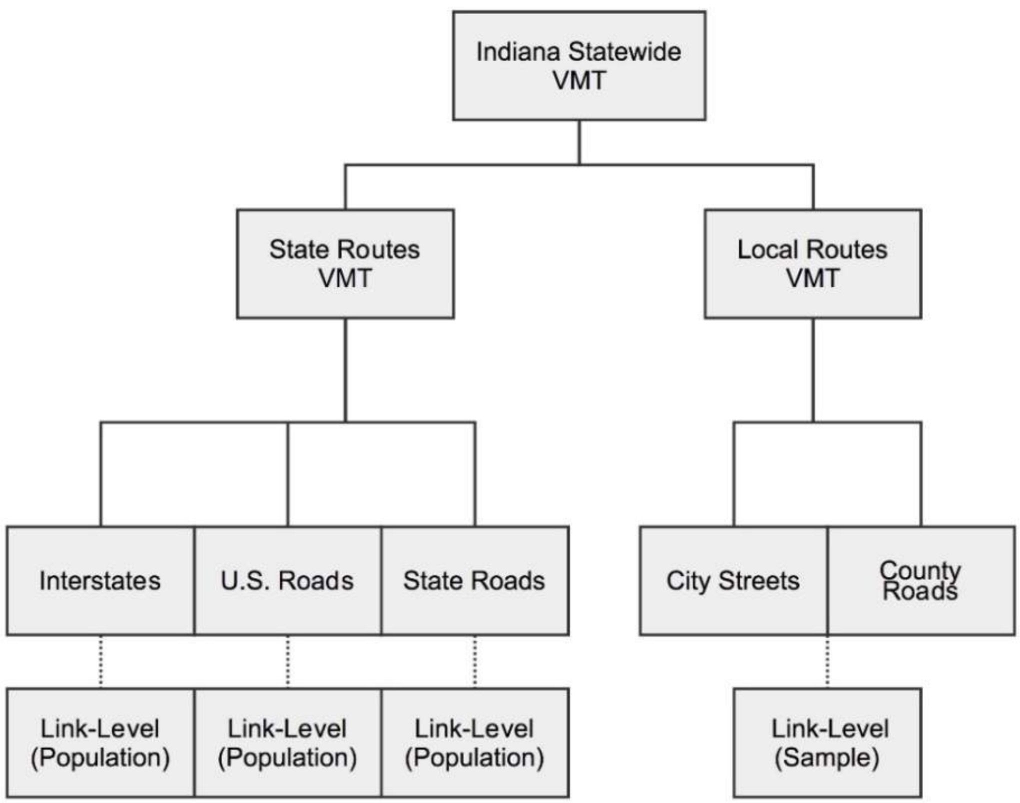


Figure 3.6 Flowchart for Statewide VMT Estimation

Time-series traffic data were available for 2009 to 2012 (Volovski et al., 2015); this allowed for VMT estimation at the link-level. These four years of traffic data are used to populate the comprehensive spreadsheet-based database developed in this research for estimation and prediction of future traffic volumes and consequently VMT. As shown in Table 3.10, an approximately 20-year horizon, 2013 to 2035, is used to provide an estimate of future VMT assuming the continuation of observed trends.

Table 3.10 Components of statewide VMT estimation and prediction

Link Level Method (Statewide VMT Estimation)			2009	2010	2011	2012	2013	…………	2035
A	State Routes (I, US, SR)	Interstates (Ramps) Interstates (Mainline) US Highways (Mainline) US & State Highways (Ramps) State Highways (Mainline)	VMT is estimated using available 2009-2012 data				VMT is predicted using growth factors based on 2009-2012 data		
		Indiana Tollroad (I-90)	VMT is estimated using available 2011 data						
B	Local Routes (City Streets & County Roads)	Cluster 1 VMT Cluster 2 VMT Cluster 3 VMT Cluster 4 VMT Cluster 5 VMT Cluster 6 VMT Cluster 7 VMT Cluster 8 VMT	VMT is predicted (backward) using growth factors based on 2012-2014 data			VMT is estimated using available 2012-2014 data		VMT is predicted using growth factors based on 2012-2014 data	
C	All Routes	Statewide Annual VMT	C = A+B	C = A+B	C = A+B	C = A+B	C = A+B	C = A+B	C = A+B

Applying observed growth factors by functional class allowed for AADT prediction (and subsequently VMT prediction) at the segment or link-level for state routes. A sample of time-series traffic counts from MACOG is used to develop a growth factor specific to local routes, as defined in this study.

The Indiana Tollroad (I-90), while not operated by INDOT, has link-level traffic data available for 2011. This year's traffic data is used as a placeholder for the remaining years (2009, 2010, and 2012) to ensure consistency when comparing aggregate VMT estimates at the statewide level.

The VMT for local routes, discussed in Section 3.4.3, was estimated using cluster groups representing all 92 Indiana counties. The available data most closely represents 2013 data and is indicated as available in Table 3.10. The total statewide VMT "C" is the summation of components "A" and "B", representing state and local routes, respectively, for the entire Indiana state highway system.

3.4.2 State Routes Framework

Separating statewide VMT estimation into two components was necessary because Interstates, US Roads, and State Roads have extensive permanent and short-term traffic counts covering the majority of the centerline mileage network, unlike the local routes. State routes comprise the most reliable component of VMT. Interstates and many US Roads have continuous coverage for all road segments.

Complete traffic data from 2009 to 2012 covers over 9,000 individual network links. Each link or highway segment has an associated length, AADT volume, functional class designation, indicator of NHS status, traffic growth factor, and vehicle class distribution. This link-level data are from INDOT's milepost designations, with additional segments created for those with missing traffic data. This allows for a continuous AADT/VMT coverage for all state routes.

To represent vehicle class distributions for all segments, sampling procedures from SPR 3704 (Volovski et al., 2015) were used as a building block to develop a database representing vehicle class percentages for all state route segments. The data collection and compilation for state routes is discussed in Section 3.5.2.

This VMT estimation framework provides significantly more detail than the non-traffic methods of VMT estimation, by allowing for the aggregation over the area of interest, such as district, county, route, statewide, and economic region.

3.4.3 Local Routes Framework

Local routes are county roads and city streets owned and operated by county and municipal governments. These are public roads that fall outside the domain of state-owned roads (interstate, US roads, and state roads), privately-owned roads, and national park roads. In Indiana, as with most states, local roads constitute a majority of the entire road network. The Indiana Local Technical Assistance Program (LTAP) estimated that 46% of the state's total VMT was attributable to local roads (Indiana Local Technical Assistance Program, 2009). However, there is a lack of a comprehensive program for traffic data collection on these roads. In this study, three main problems with existing local road VMT estimation were observed as follows:

1. First, for many local roads, the availability of adjusted traffic counts is inconsistent. This study observed that some organizations collect extensive 48-hour adjusted AADT coverage counts on an annual or periodic basis; others have unadjusted 24-hour counts; some use HPMS defaults for federal-aid eligible roadways; and the rest use none of these.
2. The second problem is that, for counties with available data, many segments of the road network often do not have counts that are required for VMT estimation at a regional level. An example of the gap in traffic counts coverage for the local road network (Tippecanoe County) and a city road network (Greater Lafayette-West Lafayette), is shown by Figure 3.7 and Figure 3.8, respectively, where light shading represent segments with unavailable data.
3. Third, close inspection of traffic counts data reveals that the selected sites are often in close proximity to urban areas, city boundaries, primary avenues or

thruways, and other important sites. When expanded to a regional level, the use of these traffic counts may introduce bias and lead to inaccurate estimations of VMT.

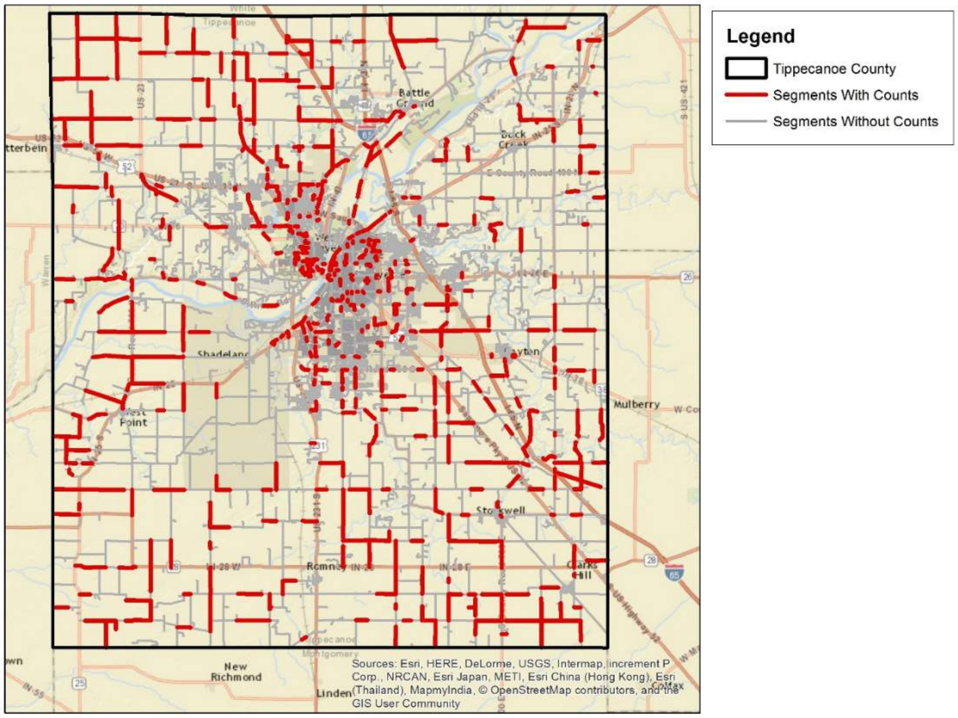


Figure 3.7 Traffic count coverage for an example local road network

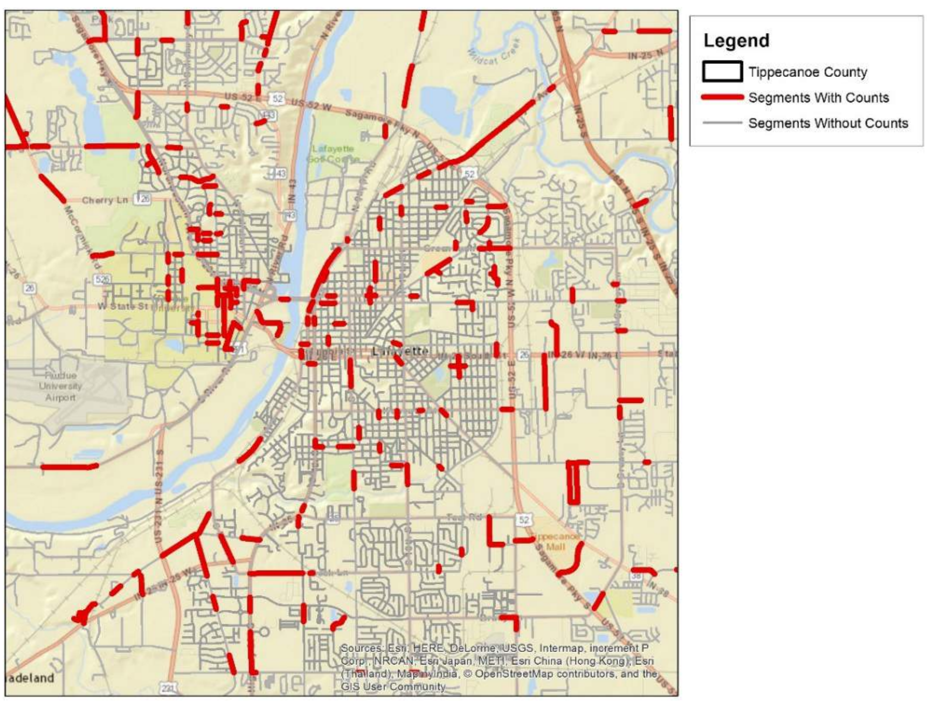


Figure 3.8 Gap in traffic counts coverage for an example city road network

To account for these three problems associated with local road VMT estimation, the following framework was developed for this study, as shown in Figure 3.9. Local roads are estimated with a sample of adjusted AADT traffic counts from counties in differing geographic areas. There are three identified estimation approaches for this study. All approaches are expanded to represent statewide VMT by statistical cluster analysis. Cluster analysis, as applied for this study, allowed for counties with similar VMT-related characteristics to be grouped together.

1. The first, an average of all the sample of traffic counts is used to develop a VMT per mile (unit value), that is expanded to the population by using a known roadway inventory mileage. This approach may not account for the heterogeneous nature of the local roads network, as discussed subsequently in Section 4.3.3 of this thesis.
2. The second, an average of the sample of traffic counts within developed road classes, similarly produces a unit value of VMT per each road class. However, this unit value uses a form of stratified sampling to more accurately represent the average within each similar road class. This is expected to be more accurate than the average approach without segmentation.
3. The third, spatial interpolation uses weighted distance techniques to interpolate AADT values for all road segments. Implemented, with spatial analyst tools of a GIS platform, this uses algorithms such as Kriging, inverse distance weighting, natural neighbor, and trend. This approach is more appropriate for estimating traffic counts at locations without ground counts in a specific county. Spatial interpolation may be appropriate for MPOs and other organizations with incomplete traffic counts for its local routes.

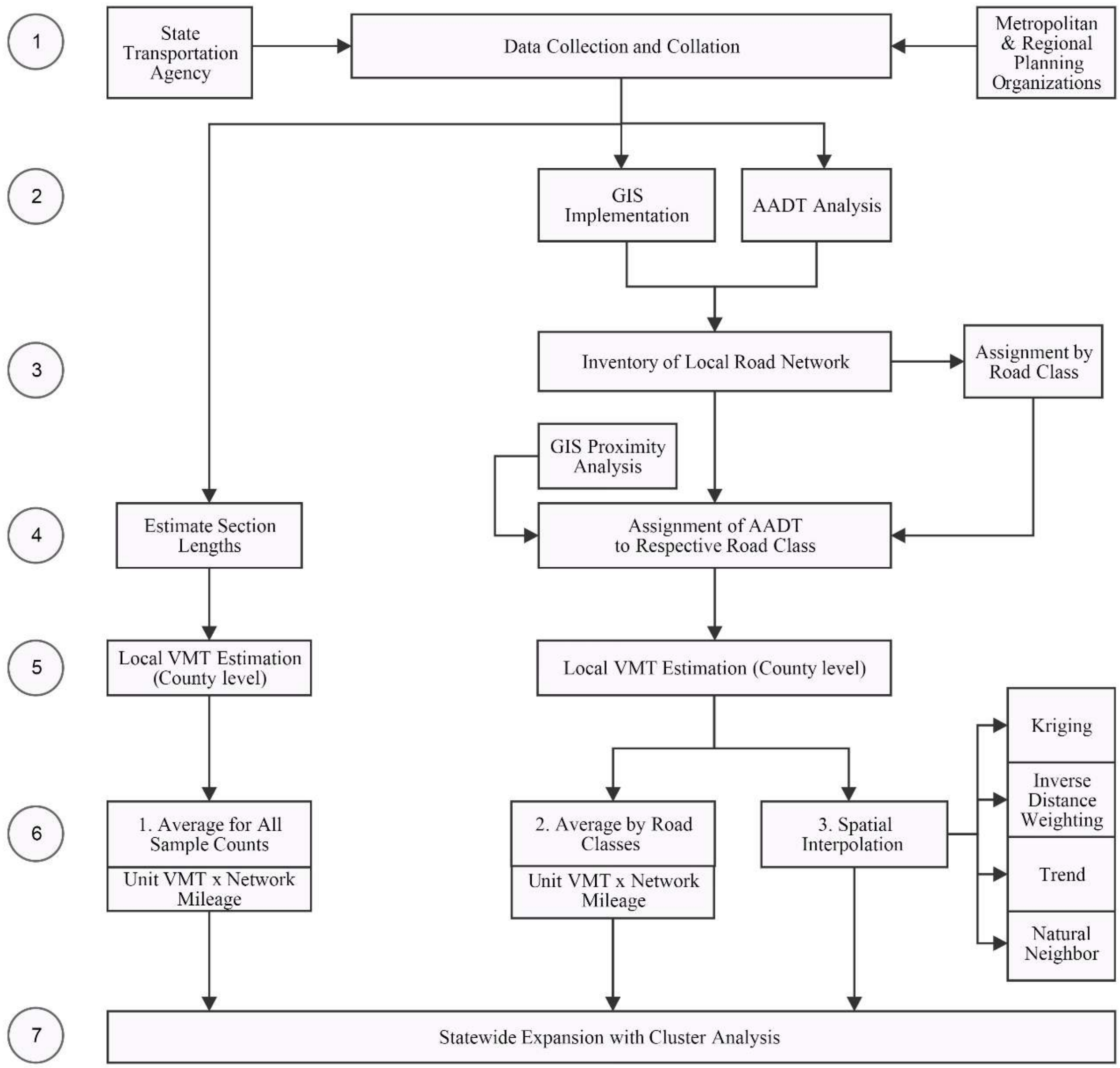
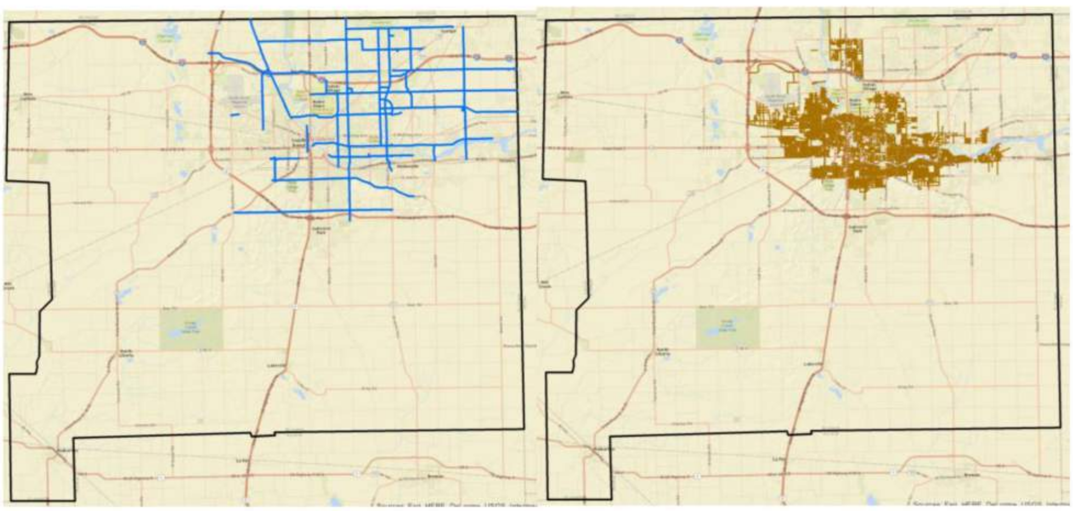


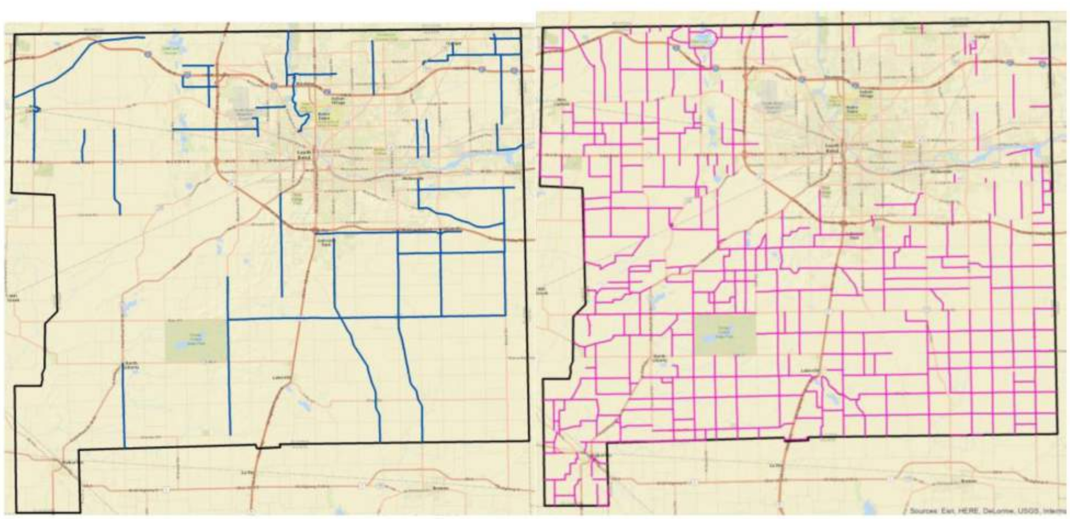
Figure 3.9 Flowchart for Local Routes VMT Estimation

For the average by road classes and spatial interpolation approaches, “road classes” for the local road network are developed. These provide more detail and a basis for adjusting the estimates from the average approach. A crucial step is the inventory of the local road network and assignment by road classes. This required implementation with a GIS platform and analyzing AADT distributions to determine the selection criteria.

Five road classes were created for local routes at the county level. The definitions for these volume groups include the following, based on the analysis in 4.3.2. County roads low volume has traffic of less than 1,000 AADT; county roads high volume has traffic of greater than 1,000 AADT; city streets low volume has traffic of less than 5,000 AADT; city streets high volume has a traffic volume of greater than 5,000 AADT; neighborhood roads have an AADT of 100-300. These four road classes containing over 95% of the data are shown for St. Joseph County in Figure 3.10.



(A) City Streets High-Volume (B) City Streets Low-Volume



(C) County Roads High-Volume (D) County Roads Low-Volume

Figure 3.10 Road classes created for a sample county

Varying designation of urban and rural areas in Indiana (Waldorf, 2007), as well as other states, may limit the effectiveness and accuracy of grouping counties based on rurality or urbanity alone in order to estimate statewide VMT. A sample of 14 counties traffic counts was obtained, and an expansion to all 92 Indiana counties comprising of the population is required. Statistical cluster analysis, as discussed in Section 3.5.2, was selected to group counties with expected similar VMT-characteristics, as compared to solely based on population and land-area type. Cluster analysis allowed for a database of over 15 variables, specific to each of Indiana's 92 counties (US Census, 2010) to be developed based on variables which drive VMT, such as mean household income, total state population, unemployment rate, per capita income, passenger car registrations, rural population, population density, housing density, percentage of single occupant drivers, percent of workers carpooling to work, percent of workers taking public transit, mean travel time to work, and number of vehicles available in household.

These clustering criteria variables were modeled using Minitab 17 software, a common statistical package, to group Indiana counties. Options selected for clustering observations included Euclidean distance, complete linkage and average linkage (producing same clusters), and specifying a final partition of eight clusters. Clusters of size exceeding 8 were not selected because representative traffic data is required for each cluster, with predominantly rural counties lacking traffic counts. The large amount of rural counties would prove cumbersome to obtain reliable and timely traffic counts to represent the local road network.

3.4.4 Vehicle Class Distributions

Separate vehicle class distributions were developed for local routes and state routes. Data are available for 2009 to 2012; 2013 to 2035 were assumed to have the same vehicle class distribution as the 2009 to 2012 average. The observed trends from 2009 to 2012, did not indicate significant variation in the relative distribution of vehicles at the statewide level. The vehicle classifications were determined using methods developed in the recently completed JTRP SPR-3704 study (Volovski et al., 2015), which utilized weighted-distance methods with Kriging spatial interpolation to estimate vehicle distributions.

Continuous segment-by-segment traffic data was unavailable for the many local roads; however, NHS Non-interstate (mainline and ramps) and Non-NHS data, reported to the HPMS for non-INDOT owned routes was available and used to develop vehicle class distributions specific to local routes. Data for local routes was unavailable for 2009, but assumed to have the same proportions as 2010, with 2010 to 2012 exhibiting minimal variation in the traffic stream. The overwhelming majority of vehicles on local routes was class 2 automobiles.

The state route vehicle class distributions are shown in Table 3.11 (Volovski et al., 2015). Personal VMT (classes 1 to 3) comprising 81.02% (2010) to 87.00% (2011) of the traffic stream, with commercial VMT comprising 13.00% (2011) to 18.98% (2010). The vehicle class distributions for local routes are shown in Table 3.12 (Volovski et al., 2015). The distribution of commercial vehicles on local roads changed from 5.94% (2010) to 7.23% (2012) over the analysis period. The overwhelming majority of local road travel is from non-commercial travel. Class 9 trucks constitute the majority of the commercial travel, with combination trucks comprising approximately 0.50% of commercial travel on local routes.

These variations between the vehicle class distributions for state and local routes emphasize the need for segregating the data. Vehicle class distributions are applied separately for state and local routes. The state route VMT is distributed using data presented in Table 3.11 and the local route VMT is distributing using data presented in Table 3.12.

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Table 3.11 State routes vehicle class distributions from segment level data

FHWA Vehicle Class	2009	2010	2011	2012	2013	………	2035
Class 1: Motorcycles	0.49%	0.49%	0.52%	0.50%	0.50%	0.50%	0.50%
Class 2: Passenger Cars	58.56%	58.43%	62.80%	60.72%	60.13%	60.13%	60.13%
Class 3: Pickups, Panels, Vans	22.11%	22.10%	23.67%	22.92%	22.70%	22.70%	22.70%
Personal VMT: Classes 1-3	**81.16%**	**81.02%**	**87.00%**	**84.15%**	**83.33%**	**83.33%**	**83.33%**
Class 4: Buses	0.28%	0.28%	0.23%	0.27%	0.27%	0.27%	0.27%
Class 5: Single Unit 2-Axle Trucks	3.39%	3.41%	2.79%	3.40%	3.25%	3.25%	3.25%
Class 6: Single Unit 3-Axle Trucks	0.87%	0.88%	0.76%	1.07%	0.89%	0.89%	0.89%
Class 7: Single Unit 4+ Axle Trucks	0.24%	0.24%	0.21%	0.32%	0.25%	0.25%	0.25%
Class 8: Single Trailer 3-4 Axle Trucks	1.08%	1.09%	0.79%	0.98%	0.99%	0.99%	0.99%
Class 9: Single Trailer 5-Axle Trucks	12.32%	12.43%	7.65%	9.26%	10.42%	10.42%	10.42%
Class 10: Single Trailer 6+ Axle Trucks	0.16%	0.16%	0.12%	0.15%	0.15%	0.15%	0.15%
Class 11: Multi-Trailer 5 Axle Trucks	0.32%	0.31%	0.20%	0.26%	0.28%	0.28%	0.28%
Class 12: Multi-Trailer 6-Axle Trucks	0.12%	0.11%	0.07%	0.09%	0.10%	0.10%	0.10%
Class 13: Multi-Trailer 7+ Axle Trucks	0.05%	0.05%	0.19%	0.05%	0.08%	0.08%	0.08%
Commercial VMT: Classes 4-13	**18.84%**	**18.98%**	**13.00%**	**15.85%**	**16.67%**	**16.67%**	**16.67%**

Table 3.12 Local routes vehicle class distributions from segment level data

FHWA Vehicle Class	2009	2010	2011	2012	2013	………	2035
Class 1: Motorcycles	0.60%	0.60%	0.59%	0.59%	0.60%	0.60%	0.60%
Class 2: Passenger Cars	65.73%	65.73%	64.75%	64.87%	65.27%	65.27%	65.27%
Class 3: Pickups, Panels, Vans	27.73%	27.73%	27.88%	27.31%	27.66%	27.66%	27.66%
Personal VMT: Classes 1-3	**94.06%**	**94.06%**	**93.22%**	**92.77%**	**93.53%**	**93.53%**	**93.53%**
Class 4: Buses	0.08%	0.08%	0.10%	0.16%	0.11%	0.11%	0.11%
Class 5: Single Unit 2-Axle Trucks	1.22%	1.22%	1.79%	2.59%	1.71%	1.71%	1.71%
Class 6: Single Unit 3-Axle Trucks	0.63%	0.63%	1.34%	1.52%	1.03%	1.03%	1.03%
Class 7: Single Unit 4+ Axle Trucks	0.21%	0.21%	0.46%	0.52%	0.35%	0.35%	0.35%
Class 8: Single Trailer 3-4 Axle Trucks	0.47%	0.47%	0.19%	0.17%	0.33%	0.33%	0.33%
Class 9: Single Trailer 5-Axle Trucks	3.19%	3.19%	2.85%	2.22%	2.86%	2.86%	2.86%
Class 10: Single Trailer 6+ Axle Trucks	0.07%	0.07%	0.03%	0.02%	0.05%	0.05%	0.05%
Class 11: Multi-Trailer 5 Axle Trucks	0.03%	0.03%	0.01%	0.01%	0.02%	0.02%	0.02%
Class 12: Multi-Trailer 6-Axle Trucks	0.01%	0.01%	0.00%	0.00%	0.01%	0.01%	0.01%
Class 13: Multi-Trailer 7+ Axle Trucks	0.02%	0.02%	0.01%	0.01%	0.02%	0.02%	0.02%
Commercial VMT: Classes 4-13	**5.94%**	**5.94%**	**6.78%**	**7.23%**	**6.47%**	**6.47%**	**6.47%**

3.5 Data Collection for Link-Level Estimation

Two different procedures for data collection are needed for link-level estimation of VMT. The first procedure, a comprehensive database of continuous traffic counts, is developed for state routes. The second procedure, a sample of local traffic counts from differing counties of varying urbanization, is expanded to represent the state. Data collection for these procedures is discussed in this section.

3.5.1 Data for State Routes

The database and procedures to develop this framework are a continuation of the VMT estimates developed as part of the recently completed SPR-3704 highway cost allocation study (Volovski et al., 2015). Traffic volumes and VMT were important inputs for cost allocations that the research team evaluated. This is the starting point for our study and uses similar years of available traffic counts, 2009-2012, for developing statewide VMT estimates and comparing alternative methods that VMT producers may utilize.

For the state routes, the data are robust and complete. This study uses an extensive traffic database for over 9,000 state routes segments in Indiana, consisting of mainline and ramps for NHS and non-NHS routes. This database contains mileposts, traffic volumes, functional class, vehicle class, and locational identifiers. As shown in Figure 3.11 on the next page, GIS implementation layers were developed by highway category, with Interstates (upper left), US Roads (upper right), and State Roads (bottom).

Figure 3.11 State routes data displayed in GIS platform by road designation

The comprehensive database developed for this research was based predominantly on short-term coverage counts. Long-term counts are capable of providing traffic volumes by FHWA vehicle classes; however, this data was only available for 80-90 highway segments. To represent traffic volumes for the other 8,000 road segments of state routes in Indiana, short-term coverage counts were used.

The developed database is structured by route, with each route section assigned a unique identified for road segments reported to the FHWA HPMS. This data was compiled from INDOT's traffic count map (INDOT, 2015b), with new network links created for missing route segments. Limited centerline mileage adjustments are expected because the developed database covers continuous start to end mileposts for each route, comprising of over 10,000 centerline pavement miles of State Routes.

3.5.2 Data for Local Routes

Data were compiled from INDOT's traffic count database system (TCDS) and metropolitan and regional planning organizations. The Tippecanoe Area Planning Commission (TAPC) provided data for Tippecanoe County. Michiana Area Council of Governments (MACOG) provided data for northern Indiana counties of Elkhart, Kosciusko, Marshall and St. Joseph (MACOG, 2015). Indy MPO provided data for Marion County. The TCDS was used for selecting non-state-owned AADT counts by county boundaries (Indiana Department of Transportation (INDOT), 2015a). This GIS-based system easily allowed non-state-owned (local) traffic counts to be exported in spreadsheet form. An example of the polygon buffer area to select all local routes traffic counts is shown in Figure 3.12. The exported data contained information on the geographical location, AADT volume, year collected, functional class, and location descriptions.

Data warehoused in the TCDS provided coverage for both rural and urban areas throughout Indiana. However, counts for non-state owned roads (local routes) were observed to contain many counts in urban areas. To better account for possible bias from many urban traffic counts, Tippecanoe County was selected as one of the case studies to develop road classes that serve as adjustment factors of the sample of traffic counts. Along with the TCDS data, compilation of MPO and RPO counts provided additional coverage throughout Indiana.

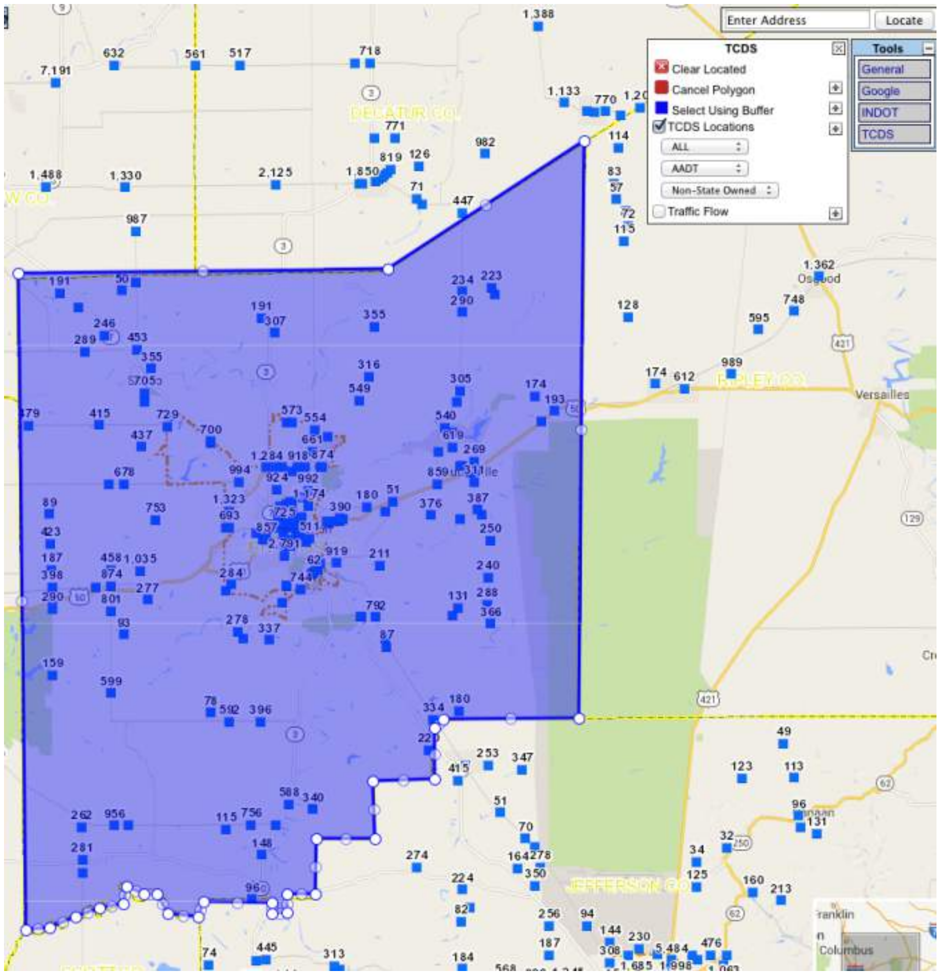

Figure 3.12 Selection of non-state owned traffic counts using the TCDS

Data was available from 14 Indiana counties and used to estimate local route VMT. These counties were selected due to the availability of local traffic data and their representativeness of the different locations of the Indiana counties, as well as representing all of INDOT’s six administrative districts. This representation is shown in Figure 3.13, with counties highlighted if they are part of the traffic count sample and the dark boundary lines representing the district boundaries. The counties contain major population centers, such as Indianapolis and Fort Wayne, as well as small-town and mixed-urban counties. The total number of traffic counts compiled per county is shown in Table 3.13, with Marion, Tippecanoe, and Lake comprising of the three largest samples.

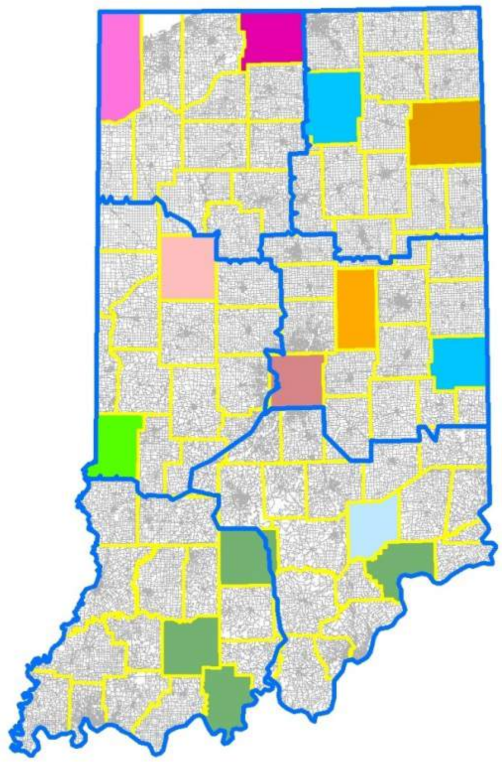

Figure 3.13 Sample of local routes traffic data by Indiana counties

Table 3.13 Summary of traffic counts sample for local routes

County	Number of Traffic Counts	Source
Marion	677	INDOT TCDS
Lake	510	INDOT TCDS
St. Joseph	455	INDOT TCDS & MACOG
Allen	192	INDOT TCDS
Tippecanoe	611	INDOT TCDS & T. APC
Madison	202	INDOT TCDS
Vigo	126	INDOT TCDS
Wayne	156	INDOT TCDS
Kosciusko	236	INDOT TCDS
Jefferson	197	INDOT TCDS
Dubois	102	INDOT TCDS
Jennings	166	INDOT TCDS
Perry	63	INDOT TCDS
Lawrence	82	INDOT TCDS

It was observed that predominately rural counties, such a Dubois, Perry, Jennings, Lawrence, and Jefferson had fewer than 200 counts. One of the challenges with local VMT is the limited counting programs and availability of data. Also, the use of these traffic counts without adjustment, may lead to misrepresentation of county-wide VMT.

3.6 Chapter Summary

This chapter provided the research methodology for this study. The desired qualities for the estimation framework, the survey of users and producers of VMT information, and the selection of the best estimation methodology were discussed. Based on the research of this study, the link-level method was selected as the control or benchmark for the comparison of the methods and for future VMT estimation is.

The framework for VMT estimation at the link and non-link levels was explained in this chapter. Link level VMT estimation consists of both the state and local route components that comprise the statewide VMT, and the vehicle class distributions were developed for link-level VMT estimation within these components. The non-link-level VMT estimation methods also were described, which include those methods using fuel revenues, trend analysis, growth factors, socioeconomic regression models, vehicle registrations, licensed drivers, and travel surveys. Finally, the data needs and collection procedures were introduced in this chapter.

CHAPTER 4. ANALYSIS AND MODELING

4.1 Introduction

This chapter uses the research methodology discussed in Chapter 3 to carry out analysis and modeling for both state and local routes, but with emphasis on local routes. To accomplish this framework, the data collection and database development procedures used in this study are further described. Once the data were collected and processed appropriately for the study, alternative VMT estimation methods were applied.

The intermediate steps and analysis to estimate local VMT using the three outlined procedures in Chapter 3 are presented in this chapter. Within the proposed local route VMT estimation framework, a sample is used, which must be expanded to represent all of Indiana. To accomplish this expansion to the population, cluster analysis was applied and is discussed in this chapter. In order to assess the resulting local VMT estimates, this study's estimates and the estimates reported in the literature are compared to gauge the extent of deviation.

One technique of local VMT estimation investigated for this study is spatial interpolation. The motivation, review of the applicable estimation techniques, and their implementation in Indiana, are provided in this chapter. Spatial interpolation relates the interconnected nature and importance of proximity in transportation. By using weighted distance techniques implemented in a GIS platform, VMT estimates for local routes are produced.

The final part of this chapter discusses the modeling inputs and components for non-link-level VMT estimation. These modeling inputs were provided by the different methods investigated in this study, such as those based on fuel, regression, licensed drivers, and vehicle registrations.

4.2 State Routes (Link-Level)

Traffic data for all mainline and ramps segments of interstates, and US and state roads are available in spreadsheet form (Excel). This comprehensive traffic database required manual processing to provide complete and consistent data for the four-year analysis period (2009 to 2012). These years serve as the baseline inventory for future year predictions and to provide for existing conditions of statewide VMT in Indiana. The user's manual developed in this study explains the information contained in the spreadsheet, discusses its updatability, and provides instructions for VMT aggregations depending on the analysis desired.

4.2.1 Database Development

An overview of the database contents include link identification information, historical traffic data, estimated annual VMT at the link level, predicted annual VMT at the link-level, vehicle class distributions at the link level, and functional class identification. This level of detail serves as the inventory for future VMT estimation. Also, the inventory is dynamic, allowing for new roads to be incorporated into the VMT estimates, such as the future Indianapolis to Evansville I-69 corridor, and any decommissioned roads to be eliminated from state highway inventory.

The data can also be filtered by route, designation, county, functional class, and economic region. For example, I-64 can be selected from routes that only aggregate the annual VMT for I-64. Aggregation is possible for the entire length or a subset of mileposts between them. A cross-section of this link-level database for a section of I-64 is provided in Table 4.1. As can be seen, I-64 from milepost 0 (Indiana-Illinois border) to milepost 61.1 was selected. Examination of the AADT and VMT, the vehicle class, and the functional class can be determined for a given route and specific highway segment.

Table 4.1 Cross-section of link-level database for interstate section

Link ID	Design.	Route	NHS-Int	Start MP	End MP	Link Length	Funct. Class	County	Econ. Region	AADT (2009)	AADT (2010)	Annual VMT (2009)	Annual VMT (2010)
1	Interstate	I64	100.0%	0	4.33	4.33	FC 1	65	11	11,060	12,580	1.75E+07	1.99E+07
2	Interstate	I64	100.0%	4.33	11.88	7.55	FC 1	65	11	10,620	12,170	2.93E+07	3.35E+07
3	Interstate	I64	100.0%	11.88	17.44	5.56	FC 1	65	11	11,510	11,450	2.34E+07	2.32E+07
4	Interstate	I64	100.0%	17.44	17.66	0.22	FC 1	82	11	12,220	12,150	9.81E+05	9.76E+05
5	Interstate	I64	100.0%	17.66	23.5	5.84	FC 1	82	11	11,781	12,899	2.51E+07	2.75E+07
6	Interstate	I64	100.0%	23.5	25.01	1.51	FC 1	26	11	12,760	12,750	7.03E+06	7.03E+06
7	Interstate	I64	100.0%	25.01	26.3	1.29	FC 1	26	11	16,330	16,230	7.69E+06	7.64E+06
8	Interstate	I64	100.0%	26.36	27.46	1.1	FC 1	82	11	16,330	16,230	6.56E+06	6.52E+06
9	Interstate	I64	100.0%	27.46	29.34	1.88	FC 1	26	11	16,330	16,870	1.12E+07	1.16E+07
10	Interstate	I64	100.0%	29.34	29.46	0.12	FC 1	26	11	17,080	17,030	7.48E+05	7.46E+05
11	Interstate	I64	100.0%	29.46	39.18	9.72	FC 1	87	11	10,719	15,729	3.80E+07	5.58E+07
12	Interstate	I64	100.0%	39.18	53.47	14.29	FC 1	87	11	10,200	15,157	5.32E+07	7.91E+07
13	Interstate	I64	100.0%	53.47	54.46	0.99	FC 1	87	11	9,580	9,560	3.46E+06	3.46E+06
14	Interstate	I64	100.0%	54.46	56.59	2.13	FC 1	74	11	13,000	12,950	1.01E+07	1.01E+07
15	Interstate	I64	100.0%	56.59	61.1	4.51	FC 1	74	11	12,250	12,420	2.02E+07	2.05E+07

4.2.2 Forecasting VMT

To forecast VMT, AADT is predicted for each road segment of the state routes database, using common growth factors by functional class. Based on the four years of data, 2009 to 2012, growth factors were developed for all state route segments based on an average of 2009 to 2010, 2010 to 2011, and 2011 to 2012, for each functional class. A growth factor for city streets and county roads was developed based on observed county level data under MACOG jurisdiction. Random sampling was used to collect data from around 150 road segments with time-series data (MACOG, 2015). Multiple year data allowed for an annual growth factor to be developed, specific to local routes.

For example, as shown in Table 4.2, mainline Interstates had 527 mainline segments for each year, with an observed mean of 1.58% for the 4-year period. Similarly, minor arterials, functional class 5, had an observed mean of 7.55%, one of the highest observed growth factors. Other descriptive statistics such as standard deviation, median, and quartiles were analyzed

Functional classes 3, 5, 6, and 7, had the highest variance. Interstates, functional class 1, are often covered by permanent stations and part of more frequent counting programs, were observed to have the lowest variance and standard deviation. For the annual growth factor, arterials and collectors had the highest standard deviation, ranging from 28.09% to 56.07%, reflecting the limited coverage counts available for these functional classes.

To account for the stochastic nature of long-term traffic forecasting, a range of VMT predictions is presented. The range is indicated by the 25% lower than the median for the lower bound, median for the average, and 25% higher than the median for the upper bound. These ranges are incorporated into the statewide VMT aggregations shown in Chapter 5. The 1st and 3rd quartile are not used for predicting because these growth factors led to predictions in 2035 which were three times greater than and less than the current level of VMT.

Table 4.2 Descriptive statistics for annual growth factors

Functional Class	Annual Growth Factor for Study	Observed Mean	Total Traffic Counts	Standard Deviation	Variation	1st Quartile	Median	3rd Quartile
State Routes								
Interstates (FC 1)	1.02%	1.58%	527	9.86%	0.97%	-1.58%	1.02%	4.69%
Principal Arterials: Major Freeways and Expressways (FC 2)	0.03%	2.45%	172	24.49%	6.00%	-3.43%	0.03%	2.83%
Principal Arterials: Other (FC 3)	1.28%	6.10%	3020	56.07%	31.44%	-2.07%	1.28%	5.86%
Major Arterials (FC 4)	1.53%	6.10%	1579	28.09%	7.89%	-1.64%	1.53%	6.22%
Minor Arterials (FC 5)	1.35%	7.55%	2757	46.53%	21.65%	-2.13%	1.35%	6.49%
Major Collectors and Locals (FC 6-7)	3.20%	8.62%	134	34.63%	11.99%	-2.23%	3.20%	10.30%
Local Routes								
City Streets and County Roads (Locals)	0.74%	1.43%	111	4.63%	0.21%	-1.41%	0.74%	3.61%

Matrices for AADT adjustment by functional class are provided in Appendix A of this thesis to facilitate the adjustment from current to future year AADT, and subsequently to develop VMT estimates. These calculations are automatically completed for the user in the spreadsheet system. The “From AADT Year” represents the year from which an AADT is desired to be adjusted. The “To AADT Year” represents the year to which an AADT is desired to be adjusted.

For example, if the user has an AADT count that was measured in 2011 for Interstates (FC 1) and desires to forecast for 2016, Table A.1 could be used to obtain the appropriate adjustment factor. This adjustment factor is multiplied by the present year AADT (in this example, 2011) to estimate the future year AADT at the given count station. The same procedure applies for any functional class comprising of state or local routes.

The annual growth factors used to develop Table A.1 to Table A.6 reflect a medium traffic growth prediction range (observing moderate VMT growth).

4.3 Local Routes (Link-Level)

A reliable benchmark for local route VMT was estimated using a sample of county-wide traffic counts. The distribution of the traffic sample was analyzed to aid with developing an estimation methodology. Based on initial estimates using an average approach without stratifying by road classes, a resulting overestimate warranted a need for developing adjustment factors. These adjustment factors were based on developing a comprehensive network inventory and estimation by created road classes. A comparison of the estimates from the study and reported values is provided. Statewide coverage is obtained through clustering analysis, by grouping counties based on VMT-related characteristics. The result from the local routes component is aggregated with the state routes component to represent statewide annual VMT.

4.3.1 Displaying Traffic Data

The traffic was compiled from INDOT, MPOs, and RPOs in spreadsheet form. Data contained a minimum of the count's latitude, longitude, station name, location description, AADT volume, collection year, and functional class. The Excel point data was brought into ArcGIS and aligned with the platform's geographic coordinate system, using Earthpoint's Excel to KMZ, Google Earth File, (Clark, 2015) conversion tool which allows the data to be easily transferable to an ArcGIS shape file in the next workflow step. This step also allows for visual inspection of the alignment of traffic counts to the correct segment. After saving the Google Earth KMZ as a KML file, this was brought into ArcGIS using the toolbox's conversion tools. The specific tool, "KML to Layer" takes the input KMZ/KML file and produces a GIS-compatible layer required for spatial analysis. The next step of VMT estimation is determining the respective segment lengths.

4.3.2 Estimating Segment Lengths

One of the problems encountered with determining local VMT from a traffic counts sample (point data) is estimating the applicable segment lengths required for VMT. Many full coverage counts from ATRs for Interstates and other higher functional classes are linked to a specific and consistent road segment using location referencing system (LRS). This allows for VMT to be quickly estimated as the product of AADT and section length. However, when working with local routes traffic data, most counts are assumed to be from intersection to intersection. This may not always be the case for much of the local routes.

Three available options were observed for determining appropriate section lengths. First, if there are records of mileposts for the specific count, then the segment length is the difference in mileposts. This is not the case for many local routes and determining this for thousands of counts is not feasible. Second, judgment can be used to measure the length using mapping software. However, this is immensely time-consuming, especially with a traffic sample of around 4,000 counts. Accuracy and reliably is also a concern. Third, spatial analyst tools within GIS can be used to determine and match the road segment to the AADT point layer. This is technically robust and time-effective for thousands of traffic counts. This option based was selected for this study.

Proximity analysis using near and join commands was applied. The near tool (ESRI, 2013) searches the database of over 645,000 road segments in Indiana to identify the closest individual road segments for each count. New entries are created in the attribute table with the identified segment and its respective length; this was joined with the AADT points layer based on the common segment identifier. This process was completed on a per county basis, for each of the fourteen counties of the traffic sample. With the AADT and section length now determined, VMT is estimated using the traffic count at each location.

4.3.3 Analysis of Traffic Sample

Using histograms, the distributions of AADT were analyzed to identify the type of distribution at the county level. It was observed that there is not a normal distribution, but a series of peaks toward extremes. A high number of observations had very low AADT, such as counts below 400, and a high AADT, such as counts greater than 8,000. The distributions for wide variety of Indiana counties, from predominantly urban, mixed urban, to predominantly rural, are shown by Figure 4.1 to Figure 4.3.

As observed from Figure 4.1, all counties in the sample had a high percentage of traffic counts with an AADT of less than 1,000. Similar observations can be drawn for predominately urban counties shown in Figure 4.2. Allen, Lake, and Marion County are skewed toward many low traffic counts, with AADT of less than 2,000. These low traffic counts may be attributed to the rural county roads, with available traffic counts compiled for this study.

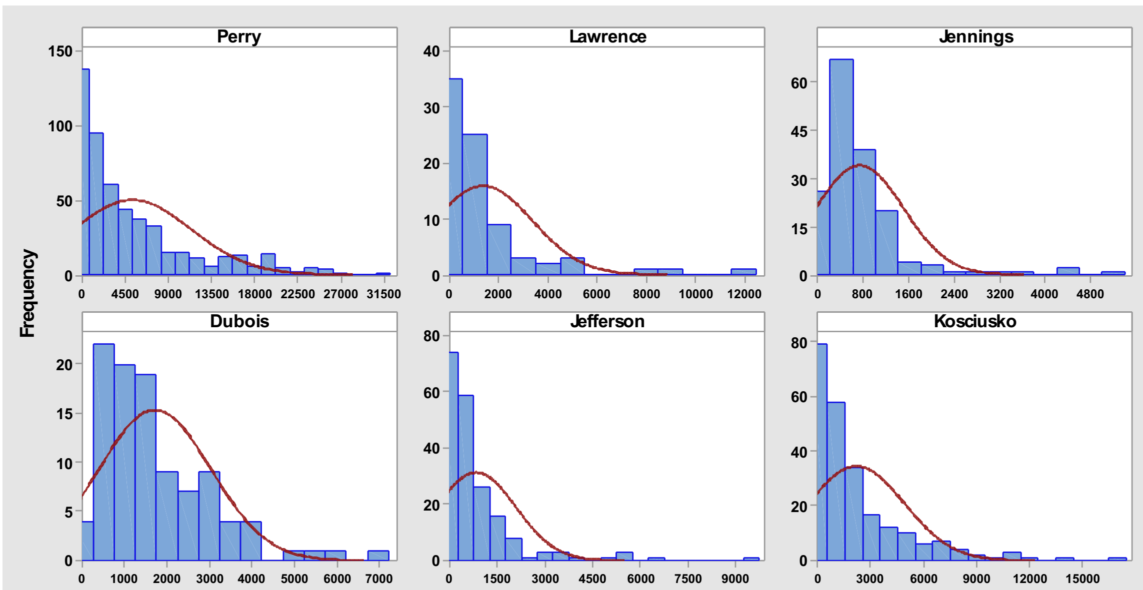

Figure 4.1 AADT distribution for local road segments in rural IN counties

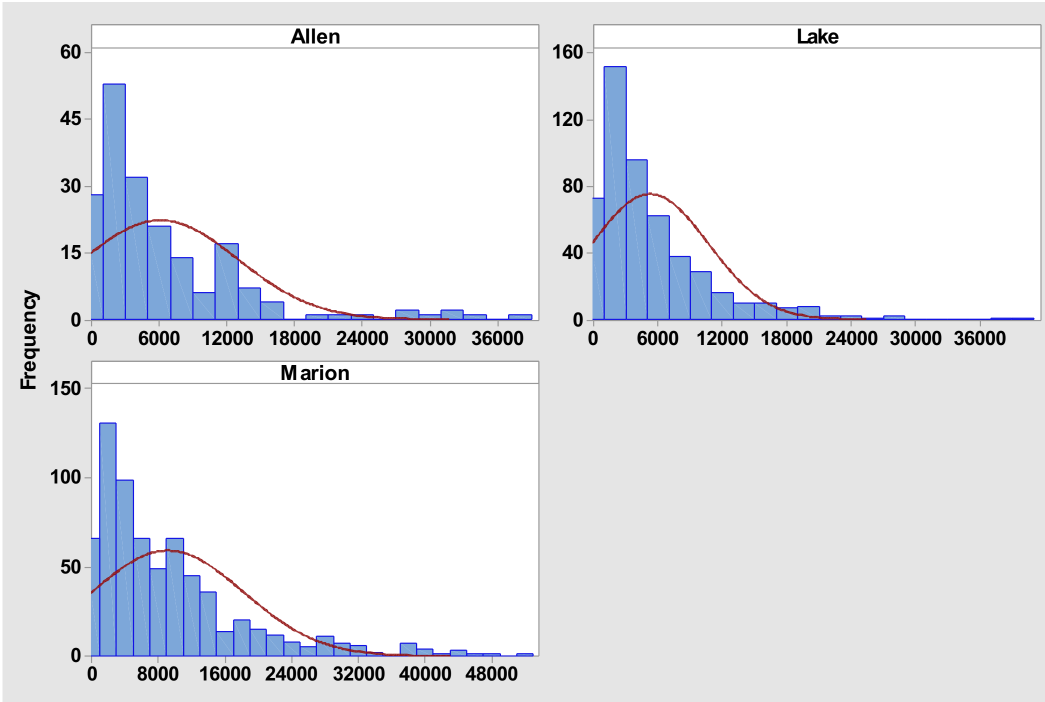

Figure 4.2 AADT distribution for local road segments in urban IN counties

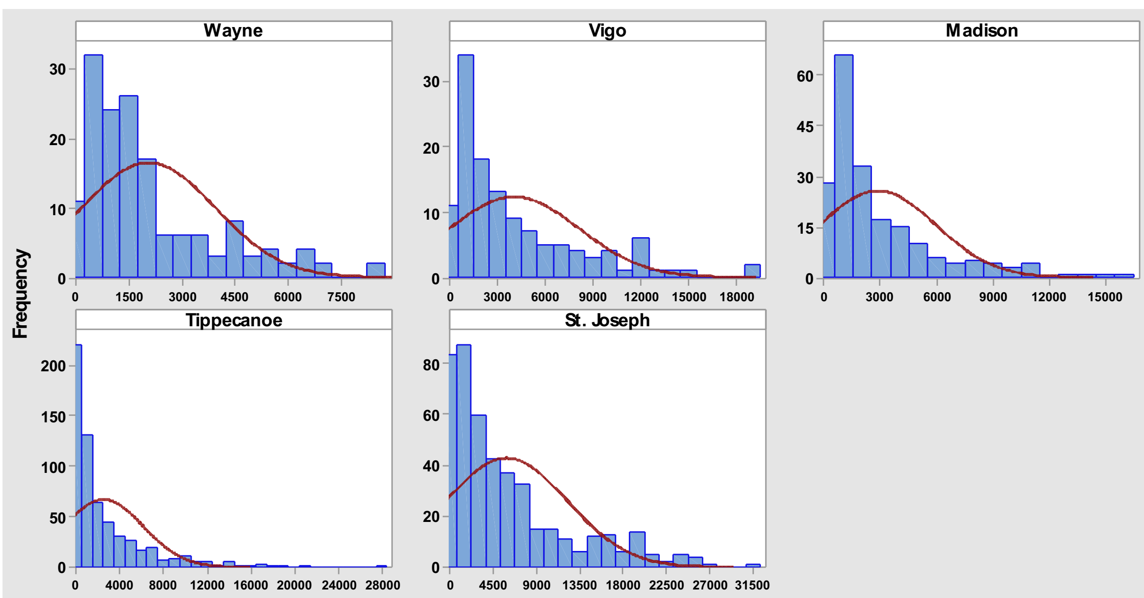

Figure 4.3 AADT distribution for local road segments in mixed urban IN counties

Finally, Figure 4.3 shows the AADT distribution for mixed urban counties such as Vigo, Madison, St. Joseph, Wayne, and Tippecanoe. Tippecanoe and St. Joseph County contained counts compiled from both INDOT and MPO data. Similar observations were made for mixed urban counties, with many low traffic counts of less than 1,000 AADT observed for St. Joseph and Tippecanoe County, in particular. The rural and urban counties presented can be drawn for mixed urban counties. These type of counties have many local routes which are outside of the city boundaries, such as low-volume county roads.

It is for these reasons that the simple average approach may produce a significant overestimate. A simple average of all data points may not represent the actual AADT distribution and over-represent cities and urban areas. County roads in the rural areas of the county are being assigned an overly high AADT when using an average AADT per mile approach with any further stratification. To avoid the introduction of bias toward "important" locations, traffic counts should be carefully selected to provide adequate county-wide coverage of all types of local roads.

4.3.4 Network Assignment by Created Road Class

Based on the analysis provided in Section 4.3.3, it is indicative that VMT estimation for all county-wide traffic counts may not be the most accurate approach. To remedy this problem, separate road and traffic networks were developed to estimate VMT more accurately.

A master inventory of local roads was developed from the homogenous road network to allow for the average AADT within each road group to be expanded based on the centerline mileage within each group. This allows for VMT to be more accurately estimated by road class and aggregated representing a county total.

The road network did not have complete attributes to allow for separation into unique networks. To remedy this, all road segments were assigned using "select by attributes" and manual selection based on observed traffic counts at the locations of these different road classes. The AADT layer was displayed to aid with the assignment and show relative magnitudes of traffic counts. The volume definitions outlined in Section 3.4.2 were the basis for this assignment. Five unique road networks were created for St.

Joseph and Tippecanoe County; and three road networks for Jefferson County. Low and high volume traffic groups were not distinguished for Jefferson County because of the limited traffic counts for this predominantly rural county. This framework for local road network assignment is presented in Table 4.3.

Table 4.3 Local routes network inventory by road class

Local Routes Traffic Sample, Mileage (No. of Links)		County: Jefferson	County: Tippecanoe	County: St. Joseph
		Rural	Mixed	Urban
Local Routes Classes	City Streets: Low Volume	40 (359)	183 (2484)	495 (6005)
	City Streets: High Volume	N/A	90 (888)	128 (877)
	County Roads: Low Volume	457 (1440)	498 (1227)	517 (933)
	County Roads: High Volume	N/A	259 (1193)	138 (431)
	Neighborhood Roads	271 (1742)	470 (4088)	511 (5319)
	All Roads	768 (3541)	1500 (9880)	1789 (13565)

The local road network was decomposed into three to five unique GIS layers, each allowing for AADT assignment based on proximity analysis. The near analysis within ArcGIS identified the road type nearest to the traffic count, within a set search radius (10 meters used). For example, there are over 600 total counts for Tippecanoe County and to determine which counts are applicable for each road class, GIS proximity analysis was used. The subset of counts, specific to the road class of interest, was selected in the attribute table and exported as a new layer. This data subset retains the attributes of the original AADT counts and allows for spatial interpolation and other analysis within ArcGIS.

For example, Figure 4.4 shows the Tippecanoe County traffic counts assigned to the unique layers of CS high volume, CR high volume, CR low volume, CS low volume, and neighborhood. Similar procedures were applied for the other counties.

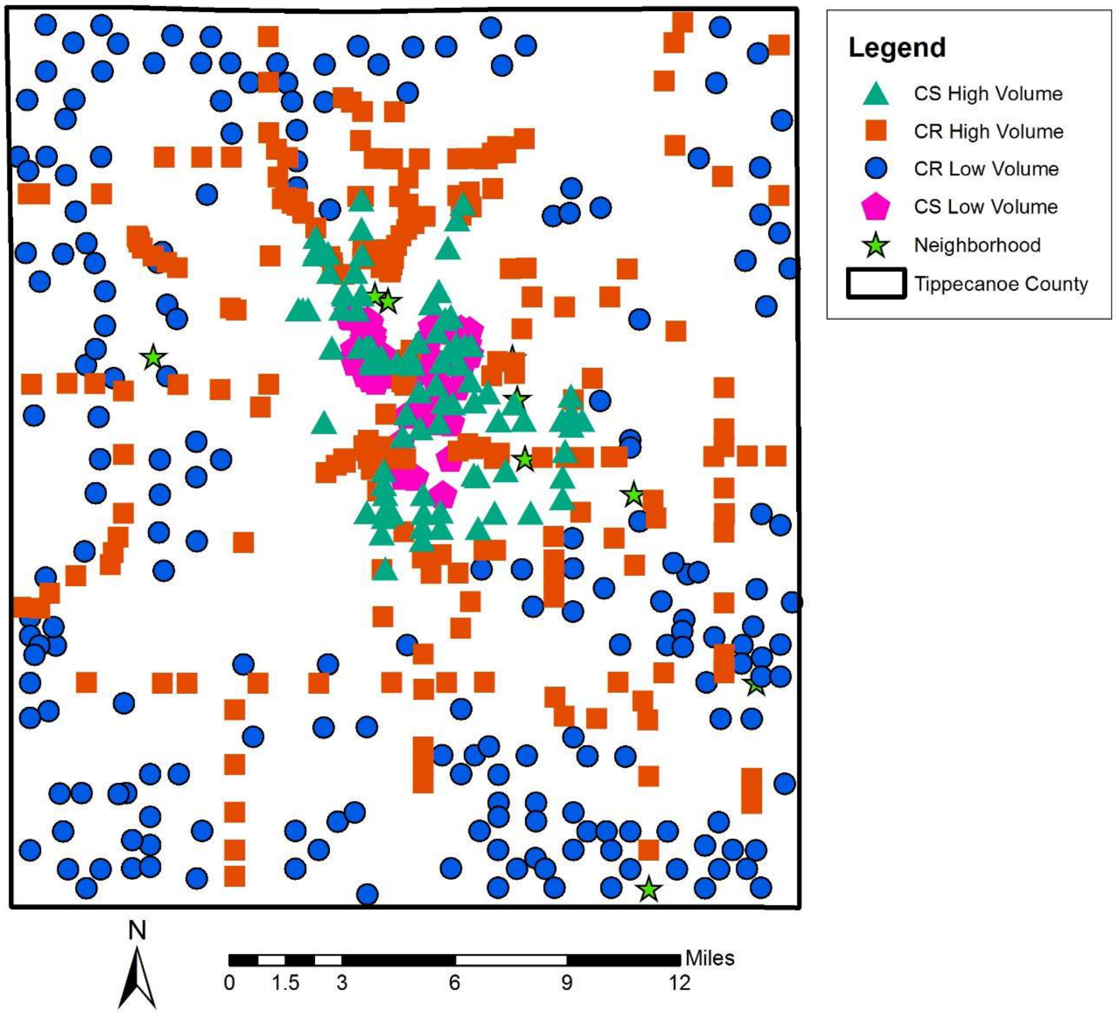

Figure 4.4 Assignment of AADT by road class for Tippecanoe County

4.3.5 Representative Counties for VMT Adjustment

To adjust the overestimates from the average without stratification approach, representative Indiana counties including Tippecanoe, St. Joseph, and Jefferson, were used. To better account for the varying degrees of urbanization throughout Indiana, separate adjustment factors are developed based on VMT estimation by road classes.

A summary of the road and traffic networks definition and estimation results by functional class, for Tippecanoe County, is given in Table 4.4. The average daily VMT per mile, per group, ranges from 154 (CR low volume) to 8,732 (CS high volume). The total annual VMT is 684.78 million, compared to 1,186.02 million from the average approach described in Section 3.4.3. This is a 73.20 percent difference, warranting an adjustment factor of 1.732.

Table 4.4 Tippecanoe County estimation results by road class

Functional Classes	Network Links	Total Roadway Mileage	Average DVMT / mile per group	Number of Traffic Counts	DVMT	AVMT
City Streets-High Volume	888	89.81	8,732	93	784,271	286,258,851
County Roads - Low Volume	1,227	497.50	154	203	76,482	27,915,979
County Roads - High Volume	1,193	258.73	2,067	223	534,792	195,199,199
Neighborhood Roads	4,088	469.62	200	9	93,924	34,282,421
City Streets - Low Volume	2,484	182.45	2,119	71	386,626	141,118,377
Totals	9,880	1498.11		599	1,876,095	684,774,828
		Total VMT from Functional Class Approach			684,774,828	
		Total VMT from Average Approach			1,186,018,256	
		Percent Difference			73.198	
		Adjustment Factor			1.732	

The distribution of the local routes county-wide VMT for Tippecanoe County is illustrated in Figure 4.5. The majority of the VMT is from CS high volume, at 42 percent, followed by CS low volume at 21 percent. Neighborhood roads and CR low volume comprise only 5 percent and 4 percent, respectively, of the total VMT of that county’s local roads.

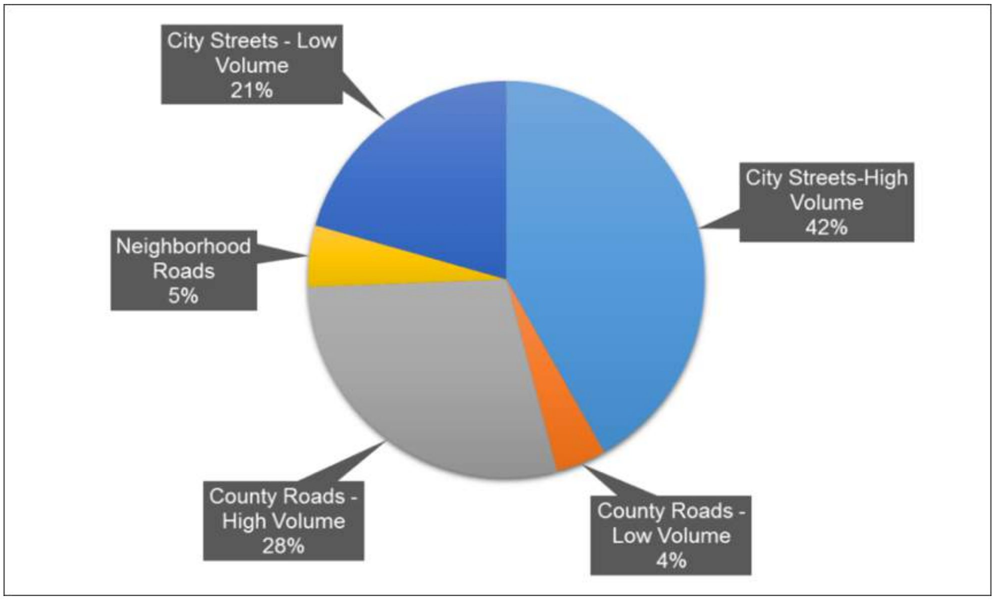

Figure 4.5 Tippecanoe County local VMT distribution

Similar methods were followed for the other two counties of the case study, St. Joseph and Jefferson. St. Joseph had higher traffic volumes, as may be intuitively expected for a more urban county than Tippecanoe. A summary of the networks definition and estimation results by road classes, for St. Joseph County, is given in Table 4.5.

Table 4.5 St. Joseph County estimation results by road class

Functional Classes	Links in Network	Total Roadway Mileage	Average DVMT / mile per group	Number of Traffic Counts	DVMT	AVMT
City Streets-High Volume	877	128.16	11,438	148	1,465,845	535,033,270
County Roads - Low Volume	933	516.53	559	116	288,632	105,350,681
County Roads - High Volume	431	138.05	2,180	80	300,960	109,850,407
Neighborhood Roads	5,319	511.46	200	22	102,292	37,336,666
City Streets - Low Volume	6,005	495.10	3,357	148	1,662,185	606,697,562
Totals	13,565	1789.30		514	3,819,914	1,394,268,586
		Total VMT from Functional Class Approach			1,394,268,586	
		Total VMT from Average Approach			4,039,912,656	
		Percent Difference			189.751	
		Adjustment Factor			2.898	

The number of traffic counts available for the county is 514. The average daily VMT per mile, per group, ranges from 11,438 for CS high volume to 559 for CR low volume. Neighborhood roads did not have directly applicable traffic counts, a low AADT was estimated for this road class. Also, the neighborhood roads component had a very low contribution to the overall total VMT.

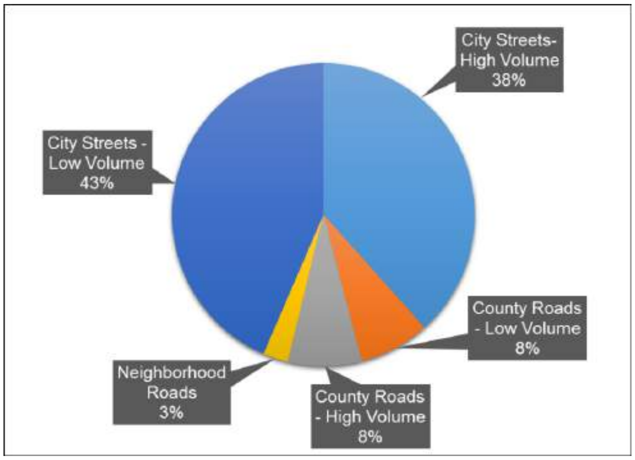

Figure 4.6 St. Joseph local VMT distribution

The total annual VMT for St. Joseph County is estimated as 1,394.27 million. This is significantly lower than the county total from an average approach, described in Section 3.4.3, of 4,039.91 million. The 189.75 percent difference warrants an adjustment factor of 2.898. The distribution of local VMT by road classes (St. Joseph County) is provided in Figure 4.6.

The final county, Jefferson, the most rural, did not have noticeable distinction between low and high-volume roads at which traffic counts are available. As shown in Table 4.6, county roads, city streets, and neighborhood roads are the three road classes analyzed. The daily VMT per mile, per group, ranged from 297 for county roads, 2,232 for city streets, to 200 for neighborhood roads. Again, an assumed value for neighborhood roads was applied. The VMT distribution (Figure 4.7) is primarily from county roads (all volume groups) at 49 percent, followed by city streets at 32 percent, and neighborhood roads comprising of 19 percent.

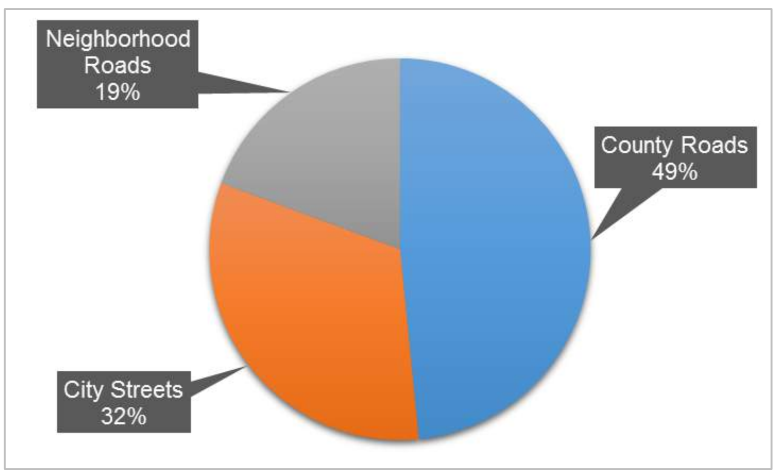

Figure 4.7 VMT distribution by road class for Jefferson County

Following a similar estimation procedure, the total annual VMT is estimated as 102.23 million. Based on the average approach for VMT estimation, described in Section 3.4.3, a county-wide VMT of 188.59 million is estimated. An 84.48 percent difference between the two approaches warrants an adjustment factor of 1.845.

Table 4.6 Jefferson County estimation results by road class

Functional Classes	Links in Network	Total Roadway Mileage	Average DVMT / mile per group	Number of Traffic Counts	DVMT	AVMT
County Roads	1,440	457.28	297	129	135,640	49,508,539
City Streets	359	40.40	2,232	51	90,175	32,914,030
Neighborhood Roads	1,742	271.27	200	0	54,255	19,802,969
Totals	3,541	768.96		180	280,070	102,225,537
			Total VMT from Functional Class Approach		102,225,537	
			Total VMT from Average Approach		188,590,095	
			Percent Difference		84.484	
			Adjustment Factor		1.845	

These adjustment factors are used to more accurately represent the county's average VMT per mile, which is expanded from the unit quantity to the county level by using the total local routes mileage. For example, the unadjusted unit VMT for Wayne County is 750,798, with an adjustment factor of 1.845 applied, becomes an adjusted unit VMT of 406,937.

4.3.6 Grouping Counties

The dendograms of Figure 4.8 and Figure 4.9 represent similarity between counties, with clusters one to seven (Figure 4.8) and cluster 8 (Figure 4.9). Cluster 8 consists of 64 predominantly rural counties, with a similarity of 94.88 percent. Cluster 1 contained Marion County by itself. Similarly, clusters 2 and 3 contained Lake and Allen County by themselves.

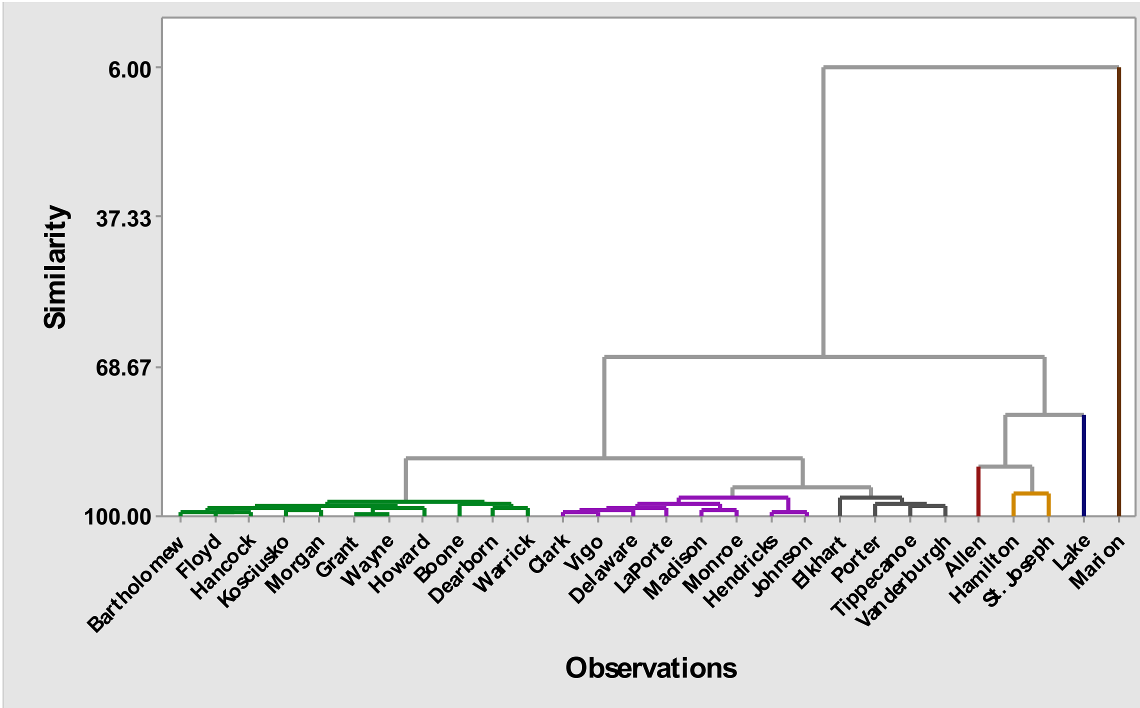

Figure 4.8 Clustering of Indiana counties based on VMT characteristics

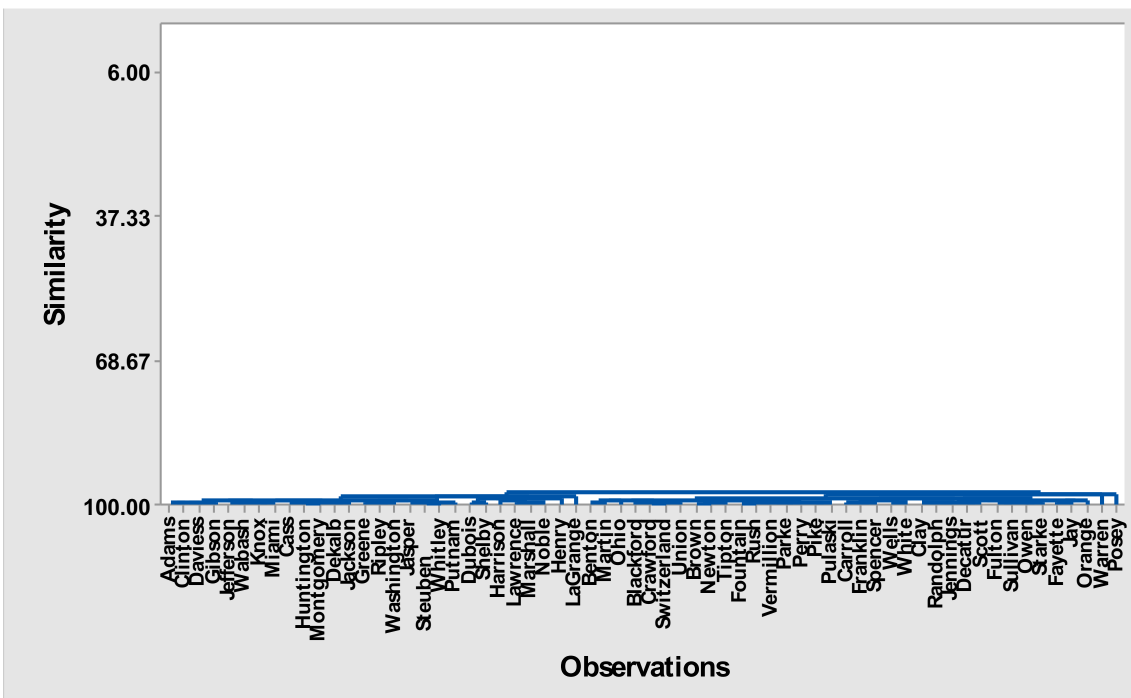

Figure 4.9 Clustering of Indiana counties (continued) based on VMT characteristics

The listing of Indiana counties assigned to the eight unique cluster groups is given in Table 4.7. The similarity was determined from statistical analysis, using the complete linkage method. The highlighted counties are part of the local roads traffic sample, with representation for each cluster group.

Table 4.7 Assignment of Indiana counties to cluster groups

Cluster Group	Similarity (Complete Linkage)	Similarity (Average Linkage)	Number of Counties	Counties			
Cluster 1	100.0%	100.0%	1	Marion			
Cluster 2	100.0%	100.0%	1	Lake			
Cluster 3	95.1%	95.1%	2	St. Joseph	Hamilton		
Cluster 4	100.0%	100.0%	1	Allen			
Cluster 5	96.0%	96.3%	4	Vanderburgh	Tippecanoe	Porter	Elkhart
Cluster 6	95.1%	96.3%	8	Johnson	Hendricks	Monroe	Madison
				LaPorte	Delaware	Vigo	Clark
Cluster 7	94.9%	96.8%	11	Warrick	Dearborn	Boone	Howard
				Wayne	Grant	Morgan	Kosciusko
				Hancock	Bartholomew	Flyod	
Cluster 8	94.9%	97.6%	64	Posey	Randolph	Martin	Whitley
				Starke	Clay	Benton	Steuben
				Owen	Spencer	Noble	Jasper
				Orange	Franklin	Marshall	Washington
				Sullivan	Carroll	Lawrence	Ripley
				Fulton	Warren	Henry	Greene
				Jay	Ohio	Shelby	Gibson
				Fayette	Vermillion	Dubois	Daviees
				White	Perry	Jackson	Clinton
				Wells	Parke	Dekalb	Adams
				Scott	Rush	Montgomery	Wabash
				Decatur	Fountain	Huntington	Jefferson
				Jennings	Tipton	Cass	Putnam
				Brown	Newton	LaGrange	Pulaski
				Union	Switzerland	Harrison	Pike
				Crawford	Blackford	Miami	Knox

4.3.7 Expansion to Statewide Estimate

The fourteen counties comprising the local roads traffic sample were used to expand from clusters to a statewide estimate. The average annual per mile was adjusted based on the adjustment factors developed in 4.3.5. The adjusted annual VMT per mile was weighted for clusters with more than one representative county. For example, Cluster 8 has traffic data from five counties and a single unit value needs to represent the total VMT.

Table 4.8 Adjusted average VMT for local routes

County	Principal Cities	Source	Years	Sample Size	Cluster Group	Average Annual VMT / Mile	Adjustment Factor	Adjusted Annual VMT / Mile
Marion	Indianapolis	TCDS	2014-2015	677	1	3,335,071	2.3147	1,440,792
Lake	Gary; E Chicago	TCDS	2014-2015	510	2	1,920,180	2.3147	829,542
St. Joseph	South Bend	TCDS	2009-2015	455	3	2,159,094	2.3147	932,755
Allen	Fort Wayne	TCDS	2014-2015	192	4	2,228,682	2.3147	962,818
Tippecanoe	West Lafayette	APC	2006-2014	412	5	415,490	1.7320	239,893
	Lafayette	TCDS	2014-2015	199	5	1,980,083	1.7320	1,143,246
Madison	Anderson	TCDS	2014-2015	202	6	1,033,744	1.8448	560,343
Vigo	Terre Haute	TCDS	2014-2015	126	6	1,465,999	1.8448	794,647
Wayne	Richmond	TCDS	2014-2015	156	7	750,798	1.8448	406,971
Kosciusko	Warsaw; Syracuse	TCDS	2009-2015	236	7	783,618	1.8448	424,761
Jefferson	Madison; Hanover	TCDS	2014-2015	197	8	302,759	1.8448	164,111
Dubois	Jasper; Dubois	TCDS	2014-2015	102	8	626,927	1.8448	339,827
Jennings	North Vernon	TCDS	2014-2015	166	8	264,396	1.8448	143,316
Perry	Derby; Tell City	TCDS	2014-2015	63	8	176,955	1.8448	95,919
Lawrence	Bedford, Mitchell	TCDS	2014-2015	82	8	499,454	1.8448	270,730

The variation between the county-wide estimates is shown in Table 4.8 is significant. Marion County has a VMT of 1,440,792 per mile, compared to rural counties with 95,919 to 339,827 per mile. The rural counties are observed to require less adjustment, with an adjustment factor of 1.85, compared to the urban counties, with an adjustment factor of 2.31.

The Total VMT per cluster group is shown in Table 4.9. The weighted average VMT per mile is necessary because of the multiple counties representing each cluster group. The VMT estimates represent 2013 statewide annual VMT because the majority of the AADT counts used for estimation are from 2012 to 2014. The statewide VMT, from local routes, is estimated as 36.214 billion, with a local road network of over 85,000 miles.

Table 4.9 Summary of VMT per cluster group

Cluster	Weighted Adjusted VMT / Mile	Local Routes Mileage	Total Adjusted VMT / Cluster
1	1,440,792	3,579	5,156,554,922
2	829,542	2,503	2,076,304,376
3	932,755	3,743	3,491,348,625
4	962,818	2,571	2,475,793,220
5	534,111	5,761	3,077,201,286
6	650,350	10,291	6,692,942,130
7	417,681	9,832	4,106,514,170
8	195,124	46,829	9,137,465,330
		85,110	36,214,124,059

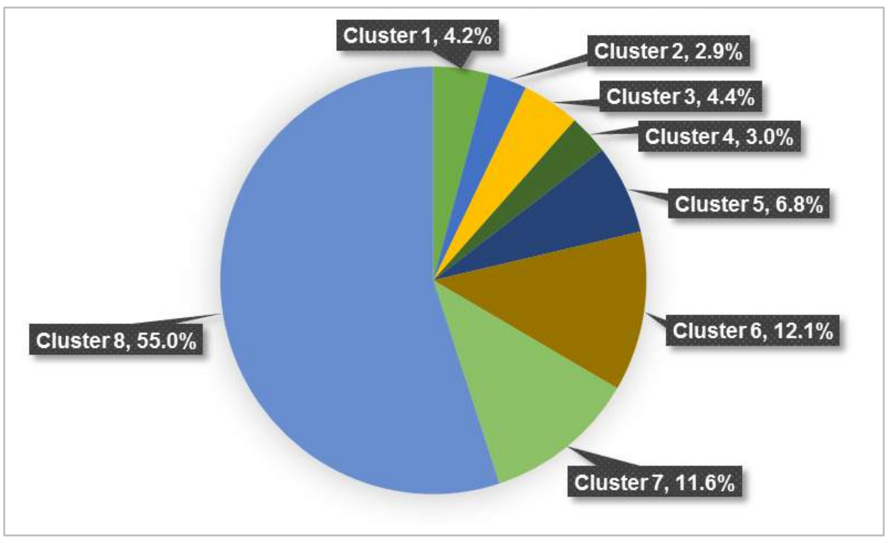

Figure 4.10 Distribution of local routes mileage per cluster group

The distribution of the road network by cluster group is shown in Figure 4.10. Cluster 8, containing the predominantly rural counties, has 55.0 percent of the total mileage, but accounts for only 25.2 percent of the total VMT. Cluster 1 has 4.2 percent of the total mileage, yet contributes 14.2 percent of the total local VMT of the state.

A graphical representation of the total local roads mileage by county is given in Figure 4.11. The data is compiled from the published INDOT historical VMT by county and systems (INDOT, 2013), for local routes consisting of both city streets and county roads (INDOT, 2013). The product of adjusted average VMT per mile and the county-wide mileages shown below represent each county’s contribution toward local VMT.

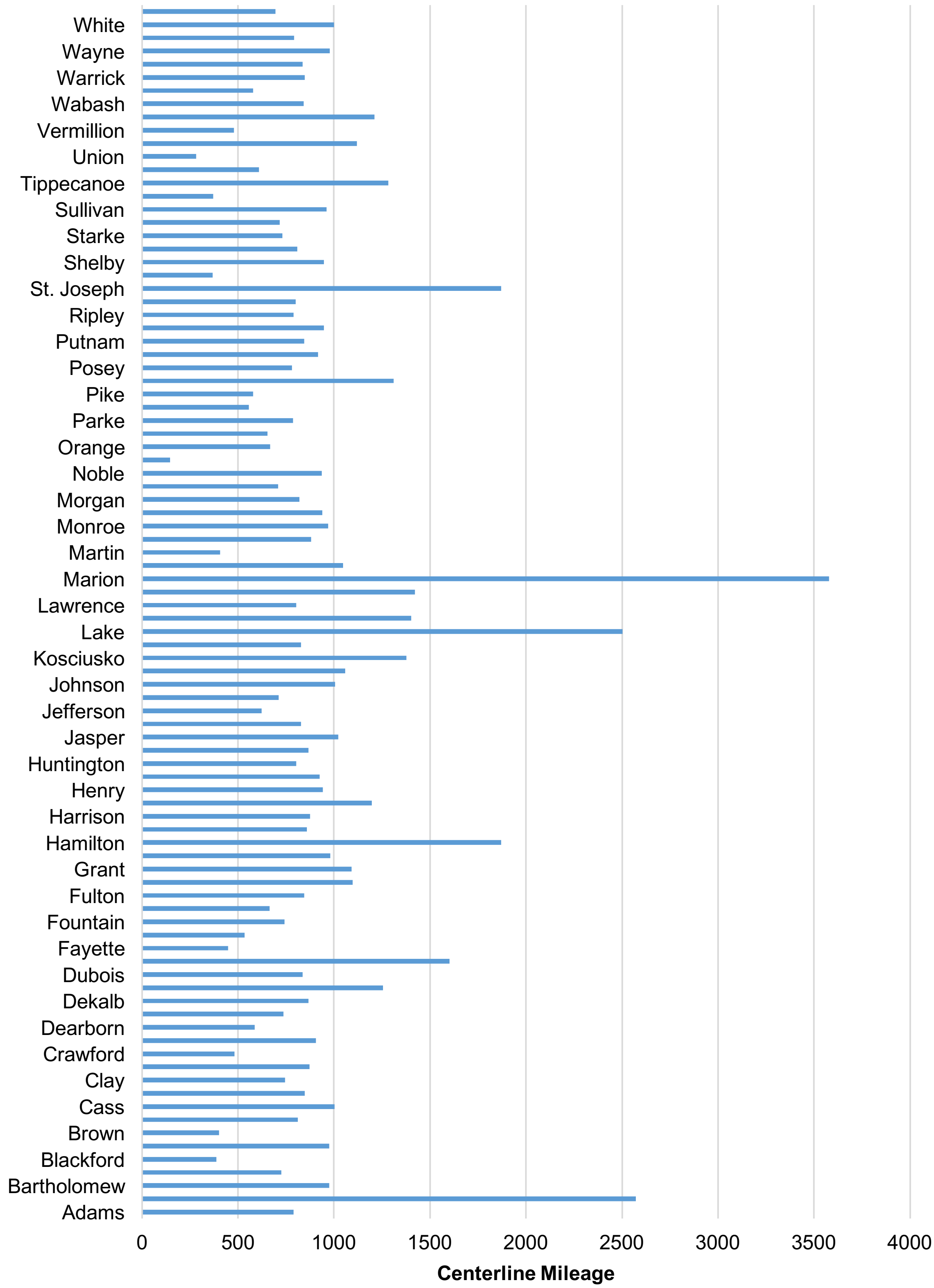

Figure 4.11 Total local routes mileage by Indiana counties

4.3.8 Comparison of Study and Literature Estimates

In this study, the estimated local routes VMT is 36.214 billion and the local road VMT from the literature (INDOT, 2013) is 38.508 billion, with data applicable for 2013. Thus, there is a 5.96 difference between the two estimates. However, there is significant variation when examining VMT for individual counties as seen from Figure 4.12. Negative percent deviations represent that the reported VMT is an underestimate, whereas positive percent deviations represent that the reported VMT is an overestimate. Findings for individual counties are given in Table 4.10.

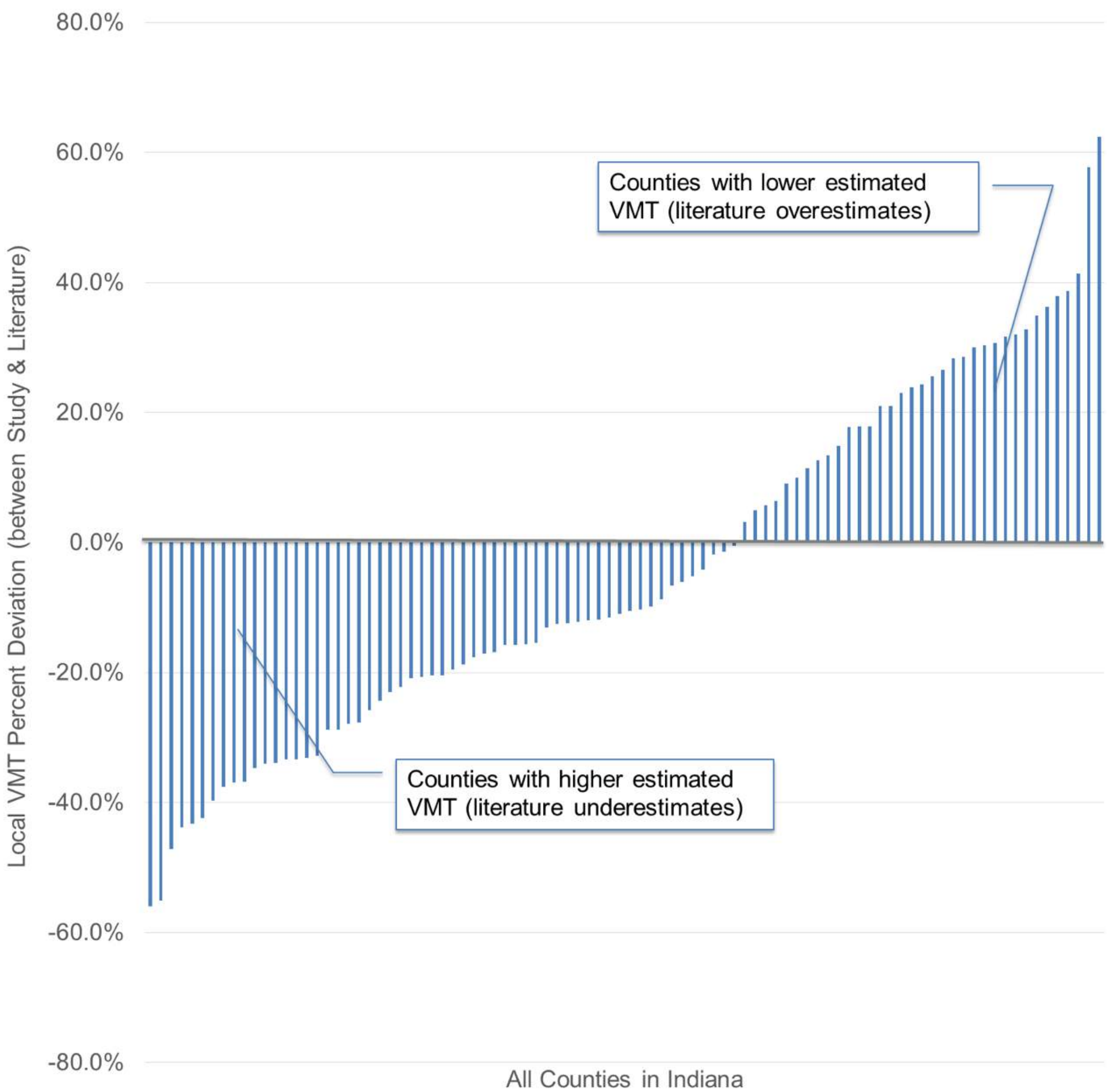

Figure 4.12 Percent deviations between study and literature local county-wide VMT

The range of difference is from -56.0% for Wayne County to 62.4% for Vanderburgh County. The reasons for such wide difference at the extremes may include the nature of assigning counties to the cluster groups and the adjusted VMT used to represent each county assigned to the cluster. Wayne and Vanderburgh, for example, are mixed urban counties which may not fit completely into one cluster. Marion County, assigned its own cluster only has a 21.0% difference between the study and reported estimates. Traffic counts and non-traffic data inputs for modeling were also extensive for Marion County. Overall, the statewide total for local roads is more reliable than estimating VMT at a disaggregate level, as may be expected.

Table 4.10 Comparison of county-wide local VMT from study and literature

County	Study AVMT (millions)	Literature AVMT (millions)	Percent Difference	County	Study AVMT (millions)	Literature AVMT (millions)	Percent Difference
Adams	154.00	143.81	-6.6%	Madison	925.38	782.20	-15.5%
Allen	2475.79	3043.74	22.9%	Marion	5156.55	6240.04	21.0%
Bartholomew	407.57	468.30	14.9%	Marshall	204.55	223.02	9.0%
Benton	141.65	88.33	-37.6%	Martin	79.40	41.98	-47.1%
Blackford	75.44	98.55	30.6%	Miami	171.68	188.71	9.9%
Boone	407.77	390.92	-4.1%	Monroe	631.11	552.25	-12.5%
Brown	78.04	62.78	-19.6%	Montgomery	183.26	167.17	-8.8%
Carroll	158.39	117.53	-25.8%	Morgan	342.83	404.06	17.9%
Cass	195.66	263.90	34.9%	Newton	138.14	87.24	-36.9%
Clark	550.70	496.40	-9.9%	Noble	182.64	171.55	-6.1%
Clay	145.49	137.97	-5.2%	Ohio	28.77	20.81	-27.7%
Clinton	170.00	141.26	-16.9%	Orange	130.30	82.13	-37.0%
Crawford	93.86	56.58	-39.7%	Owen	127.68	90.89	-28.8%
Daviess	176.86	174.47	-1.4%	Parke	153.73	133.59	-13.1%
Dearborn	244.90	206.23	-15.8%	Perry	108.36	94.90	-12.4%
Decatur	143.85	178.85	24.3%	Pike	112.82	64.97	-42.4%
Dekalb	169.34	239.44	41.4%	Porter	700.06	921.99	31.7%
Delaware	816.73	672.33	-17.7%	Posey	152.23	128.48	-15.6%
Dubois	349.75	198.56	-43.2%	Pulaski	179.14	118.26	-34.0%
Elkhart	855.94	1060.69	23.9%	Putnam	164.73	163.89	-0.5%
Fayette	238.80	107.31	-55.1%	Randolph	185.02	146.73	-20.7%
Floyd	223.24	352.23	57.8%	Ripley	154.17	121.91	-20.9%
Fountain	144.74	94.54	-34.7%	Rush	156.36	121.55	-22.3%
Franklin	129.75	116.07	-10.5%	Scott	71.80	86.87	21.0%
Fulton	164.71	131.04	-20.4%	Shelby	184.77	256.23	38.7%
Gibson	213.99	173.74	-18.8%	Spencer	157.85	119.36	-24.4%
Grant	456.35	351.13	-23.1%	St. Joseph	1745.29	1965.53	12.6%
Greene	191.59	158.78	-17.1%	Starke	142.53	95.27	-33.2%
Hamilton	1746.06	2245.12	28.6%	Steuben	139.76	192.72	37.9%
Hancock	358.48	488.37	36.2%	Sullivan	187.82	126.29	-32.8%
Harrison	170.75	121.55	-28.8%	Switzerland	72.38	47.82	-33.9%
Hendricks	778.17	1011.42	30.0%	Tippecanoe	684.77	866.51	26.5%
Henry	183.57	192.72	5.0%	Tipton	119.02	104.76	-12.0%
Howard	386.28	512.83	32.8%	Union	55.31	36.87	-33.4%
Huntington	156.95	185.06	17.9%	Vanderburgh	597.63	970.54	62.4%
Jackson	169.11	188.34	11.4%	Vermillion	93.57	83.95	-10.3%
Jasper	199.36	212.07	6.4%	Vigo	786.86	690.58	-12.2%
Jay	161.53	142.35	-11.9%	Wabash	164.27	145.27	-11.6%
Jefferson	121.54	143.08	17.7%	Warren	112.91	81.40	-27.9%
Jennings	139.05	183.60	32.0%	Warrick	353.60	297.84	-15.8%
Johnson	654.88	840.23	28.3%	Washington	163.32	172.65	5.7%
Knox	206.28	233.97	13.4%	Wayne	636.39	279.96	-56.0%
Kosciusko	575.75	383.98	-33.3%	Wells	154.59	137.61	-11.0%
LaGrange	161.42	128.48	-20.4%	White	195.20	191.63	-1.8%
Lake	2076.30	2706.84	30.4%	Whitley	135.76	170.46	25.6%
LaPorte	912.73	512.83	-43.8%				
Lawrence	156.74	161.70	3.2%				

4.3.9 Functional Class Distributions

One of the difficulties of estimating VMT by functional class is the variation within state routes and local routes for the FHWA functional class designations. Highway categories of US and State Highways have a mixture of principal arterials, minor arterials, collectors, and local designations on these roads. Based on link-level data, described in Section 3.5, the distribution of state route VMT by FHWA functional class is provided in Table 4.11.

Table 4.11 Distribution of state route VMT by FHWA functional class

FHWA Functional Class	Principal Arterials - Interstates	Principal Arterials - Other Fwys	Principal Arterials - Other	Minor Arterials	Major Collectors	Minor Collectors	Locals
	FC 1	FC 2	FC 3	FC 4	FC 5	FC 6	FC 7
Interstates	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
US Highways	0.0%	7.1%	75.7%	11.7%	5.3%	0.1%	0.0%
State Highways	0.0%	4.4%	42.7%	25.0%	26.7%	1.1%	0.1%

For local routes, those roads which comprise of city streets and county roads, the distribution of functional class VMT is difficult. The results for local routes are provided in Table 4.12, based on the 14-county traffic sample used in this study. Functional class 7, “locals” was not the functional class noted for the majority of road sections in the sample. Instead, the distribution between principal arterials, minor arterials, collectors, and locals, varied greatly. A cluster average for the six functional classes (with all of FC 1 attributed to state routes) was used to estimate a statewide total for functional classes. Cluster 1, Marion County, had the highest local VMT attributed to principal arterials, as expected for an urban area.

Table 4.12 Distribution of local route VMT by FHWA functional class

FHWA Functional Class	Principal Arterials - Other Fwys	Principal Arterials - Other	Minor Arterials	Major Collectors	Minor Collectors	Locals
	FC 2	FC 3	FC 4	FC 5	FC 6	FC 7
Allen	0.0%	20.4%	44.6%	26.2%	1.1%	7.8%
Dubois	0.0%	0.0%	25.6%	69.4%	4.8%	0.3%
Jefferson	0.0%	0.3%	20.0%	51.2%	0.1%	28.3%
Jennings	0.0%	0.0%	20.4%	66.1%	1.2%	12.4%
Kosciusko	0.0%	5.4%	27.8%	50.8%	2.4%	13.7%
Lake	1.7%	10.0%	51.4%	36.9%	0.0%	0.1%
Lawrence	0.0%	16.2%	36.5%	46.7%	0.1%	0.6%
Madison	0.0%	29.6%	27.6%	42.6%	0.0%	0.2%
Marion	6.6%	39.3%	29.9%	24.1%	0.0%	0.1%
Marion (MPO)	4.0%	80.9%	7.0%	8.1%	0.0%	0.0%
Perry	0.0%	0.0%	8.0%	81.0%	10.0%	1.0%
St. Joseph	0.0%	26.3%	40.7%	20.3%	1.0%	11.7%
Tippecanoe	0.0%	7.6%	29.7%	40.9%	6.2%	15.5%
Vigo	0.0%	9.9%	34.7%	52.3%	2.4%	0.8%
Wayne	0.0%	7.8%	31.2%	60.6%	0.2%	0.2%
Cluster 1 Average	5.3%	60.1%	18.5%	16.1%	0.0%	0.1%
Cluster 2 Average	1.7%	10.0%	51.4%	36.9%	0.0%	0.1%
Cluster 3 Average	0.0%	26.3%	40.7%	20.3%	1.0%	11.7%
Cluster 4 Average	0.0%	20.4%	44.6%	26.2%	1.1%	7.8%
Cluster 5 Average	0.0%	7.6%	29.7%	40.9%	6.2%	15.5%
Cluster 6 Average	0.0%	19.8%	31.1%	47.4%	1.2%	0.5%
Cluster 7 Average	0.0%	6.6%	29.5%	55.7%	1.3%	6.9%
Cluster 8 Average	0.0%	3.3%	22.1%	62.9%	3.2%	8.5%

4.4 Spatial Interpolation for VMT Estimation

This thesis has identified a framework for VMT estimation to establish a robust, comprehensive, and sustainable methodology for all road types. Part of the framework involves comprehensive evaluation of VMT estimation techniques. A final technique, referred to as spatial interpolation, was investigated for use in VMT estimation.

This approach assumes that the VMT at a given location is strongly and directly related to the VMT of its neighboring locations, and the strength of this relationship is proportional to the distance from its neighbors

Weighted distance algorithms are used to develop models which reliably interpolate the synthetic estimates of traffic volumes (AADT) for the road segments with unavailable, missing, or outdated data. To gauge the applicability for local jurisdictions and planning organizations, spatial interpolation was investigated in this study for a wide variety of road classes. This section discusses the motivation, review of techniques, implementation for Indiana, project level application, and suitability based on county type and local road class.

4.4.1 Motivation

Spatial interpolation may be more suitable for local roads VMT estimation because of the limited traffic counts and incomplete coverage available. This approach does not require additional traffic data, but uses existing counts warehoused by INDOT and maintained by local organizations. Therefore, no additional traffic counting resources and expense of field staff is required. The database can be updated easily when more recent or extensive traffic data becomes available. The procedure is implemented with readily-available GIS platforms (ESRI, 2013) and by using default user settings on that platform. Spatial interpolation can be viewed as a robust method of VMT estimation which is capable of providing comparative estimates from a variety of techniques.

4.4.2 Review of Techniques and Applications

Spatial interpolation techniques include inverse distance weighting (IDW), trend, topo-to-raster, spline, pointInterp, natural neighbor (NN), and Kriging (Mitas and Mitasova, 1999). PointInterp, spline, and topo-to-raster interpolation techniques were not implemented for this specific study because their underlying assumptions and the topographical challenges are not applicable. These types of techniques are more suitable for mining, forestry, and other resource-oriented fields.

Therefore, IDW, Kriging, NN, and trend interpolation were investigated for this study. IDW is used where the parameter of interest is densely populated over the area of interest. NN is used when a clustered set of traffic count data is available. Trend is an inexact estimation that uses least squares regression fitting and can be implemented only when there is minimal variation in the magnitude of the parameter of interest (Mitas and Mitasova, 1999). Where the parameter of interest is traffic count, the resulting surface from trend analysis may be appropriate only for a specific functional class of road network. Kriging is a popular geostatistical technique used in a wide range of fields such as mining (Delfiner, 1976), hydrosciences (Goovaerts, 2000), health sciences (Kelsall and Wakefield, 2002) and environmental sciences (Li and Heap, 2011).

There has been recent examination of the application of these type of techniques in the transportation engineering field. Researchers have applied Kriging algorithms for AADT prediction and vehicle class distributions (Eom et al., 2006; Volovski et al., 2015).

Of the available spatial interpolation techniques, Kriging may be the most robust because it considers the mutual interactions of all the available data in the area of interest, within a pre-defined search radius (Myers, 1994). Thus, Kriging assumes spatial correlation using weighted average techniques. Of the types of Kriging, the Ordinary Kriging method is the most commonly applied for spatial interpolation because it does not assume an underlying trend in the data, unless the dataset exhibits a clearly defined trend.

4.4.3 Implementation for Indiana

Local roads traffic data was collected for Tippecanoe, Jefferson, and St. Joseph County (Table 4.13), representing varying geographic areas and urbanization: Tippecanoe is mixed-urban, Jefferson is predominantly rural, and St. Joseph is predominantly urban. Each county and road class within the county has a different number of local AADT traffic counts. For example, the sample for St. Joseph, in this study, has 148, 80, 147, and 116 traffic counts for city streets high volume, county roads high volume, city streets low volume, and county roads low volume, respectively.

Table 4.13 Summary of traffic count sample and validation dataset

Functional Class	Average AADT	Number of AADT	Validation Dataset
Tippecanoe County			
City Streets - High Volume	8,732	93	9
County Roads - High Volume	2,067	223	21
City Streets - Low Volume	2,119	71	7
County Roads - Low Volume	154	203	18
St. Joseph County			
City Streets - High Volume	11,438	148	15
County Roads - High Volume	2,180	80	8
City Streets - Low Volume	3,378	147	15
County Roads - Low Volume	559	116	11
Jefferson County			
County Roads - Low Volume	297	129	13
City Streets - Low Volume	2,232	51	5

Spatial interpolation techniques produce raster surfaces for one road class at each time. Each technique uses the AADT value as the surface height or Z-value to produce a “rastervalue” which represents the interpolated AADT. To estimate VMT, the continuous variation of AADT across the study area is applied to the road networks. An example of Kriging interpolation for all road classes, to show variation of AADT across a county is illustrated from Figure 4.13. However, higher accuracy is expected when producing the interpolation surfaces for one road class at a time, with the traffic counts specific to the road class in consideration. As observed from Figure 4.13, the highest interpolated AADT value is 11,604 and the lowest is 41, with low traffic volumes typically seen as being representative of rural county roads. This is one example of the linkage between the continuous AADT surfaces from weighted distance analysis, and the county’s road network. The same process could be done for a specific city or township within the county, if the road network is defined by attributes allowing for selection within boundaries.

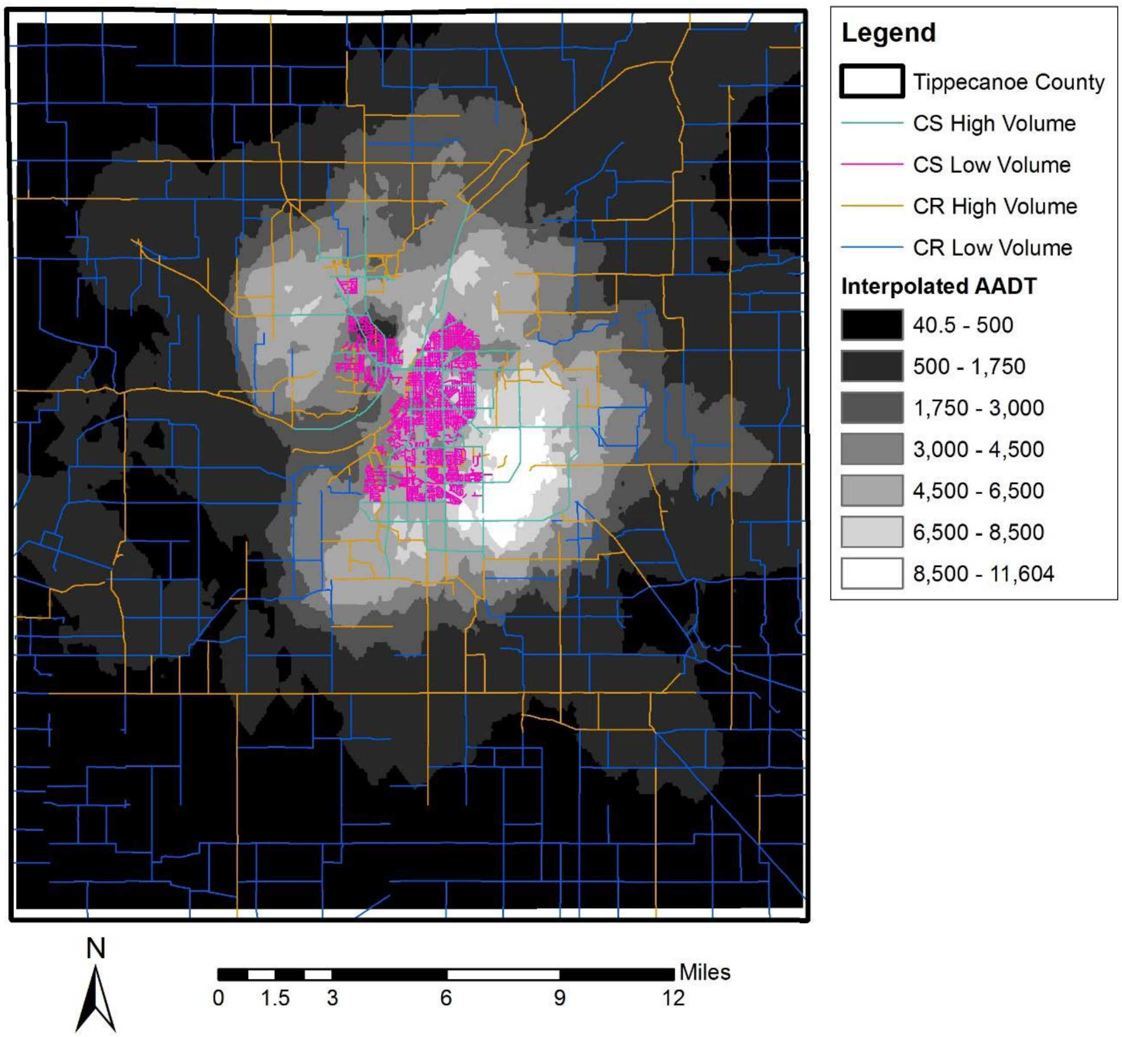

Figure 4.13 Interpolated AADT raster surface for Tippecanoe County

VMT is estimated for every link in the road inventory by developing a centroid for every segment as shown in Figure 4.14 for Tippecanoe (top) and St. Joseph (bottom). This continuous VMT represents all centerline mileage of the road network.

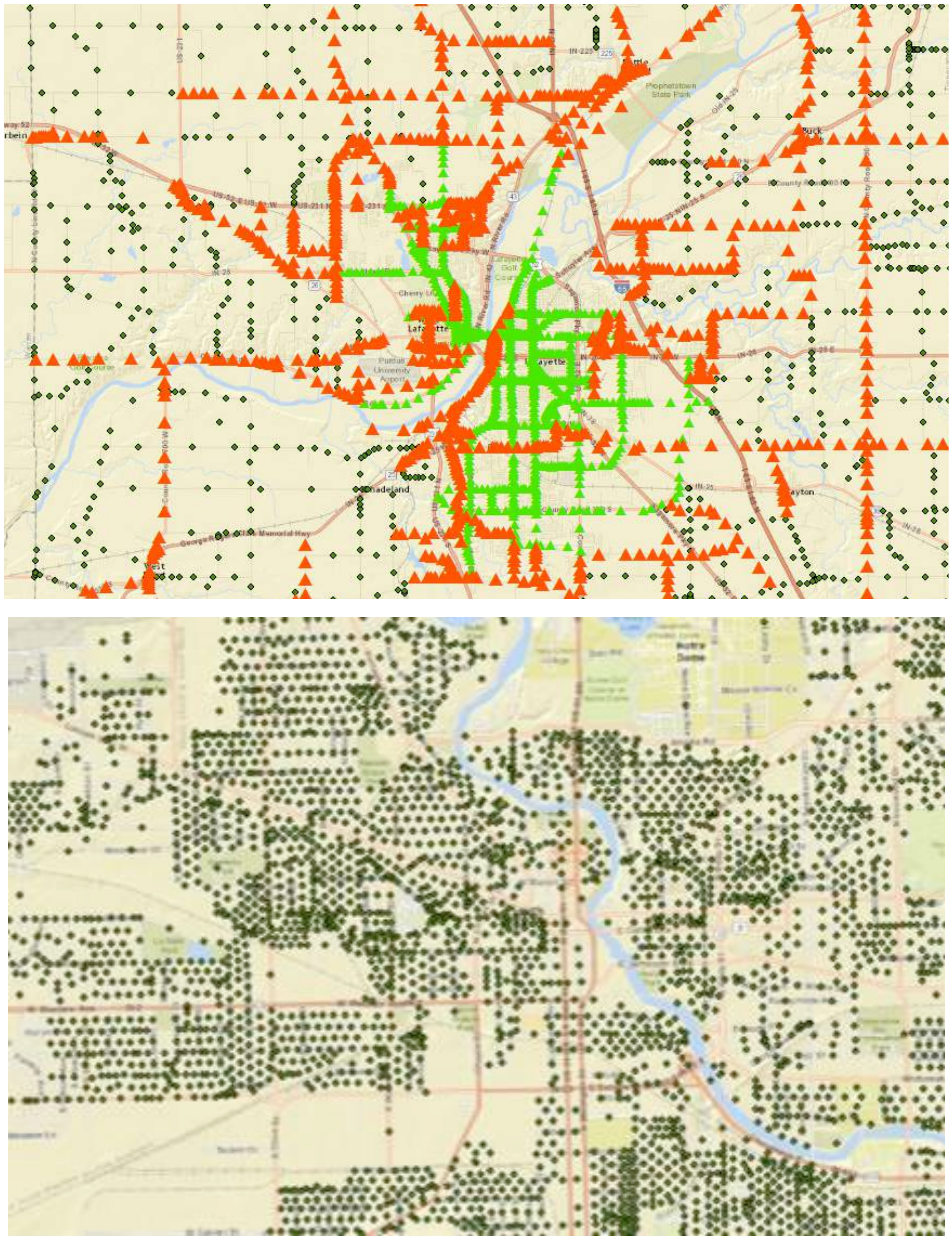

Figure 4.14 Assignment of interpolated AADT based on road class centroid

This allows the AADT from the surface to be assigned to the appropriate segment, creating a joined database of the entire county's local road network. The VMT is then calculated as the sum of the VMTs of individual links over the area of interest, in this case, the county in question.

As shown in Figure 4.15, a continuous traffic volume map can be developed for a specific road class from the interpolated AADT surface. The lowest interpolated AADT for high volume city streets is 4,260 and highest is 18,977. High-volume city streets are shown for a section of West Lafayette and Lafayette. One can assess areas of high VMT, such as the avenues and boulevards (high volume city streets) shown in Greater Lafayette, with the highest volume occurring on roads indicated with thick shading representing 15,000 to 18,977 AADT.

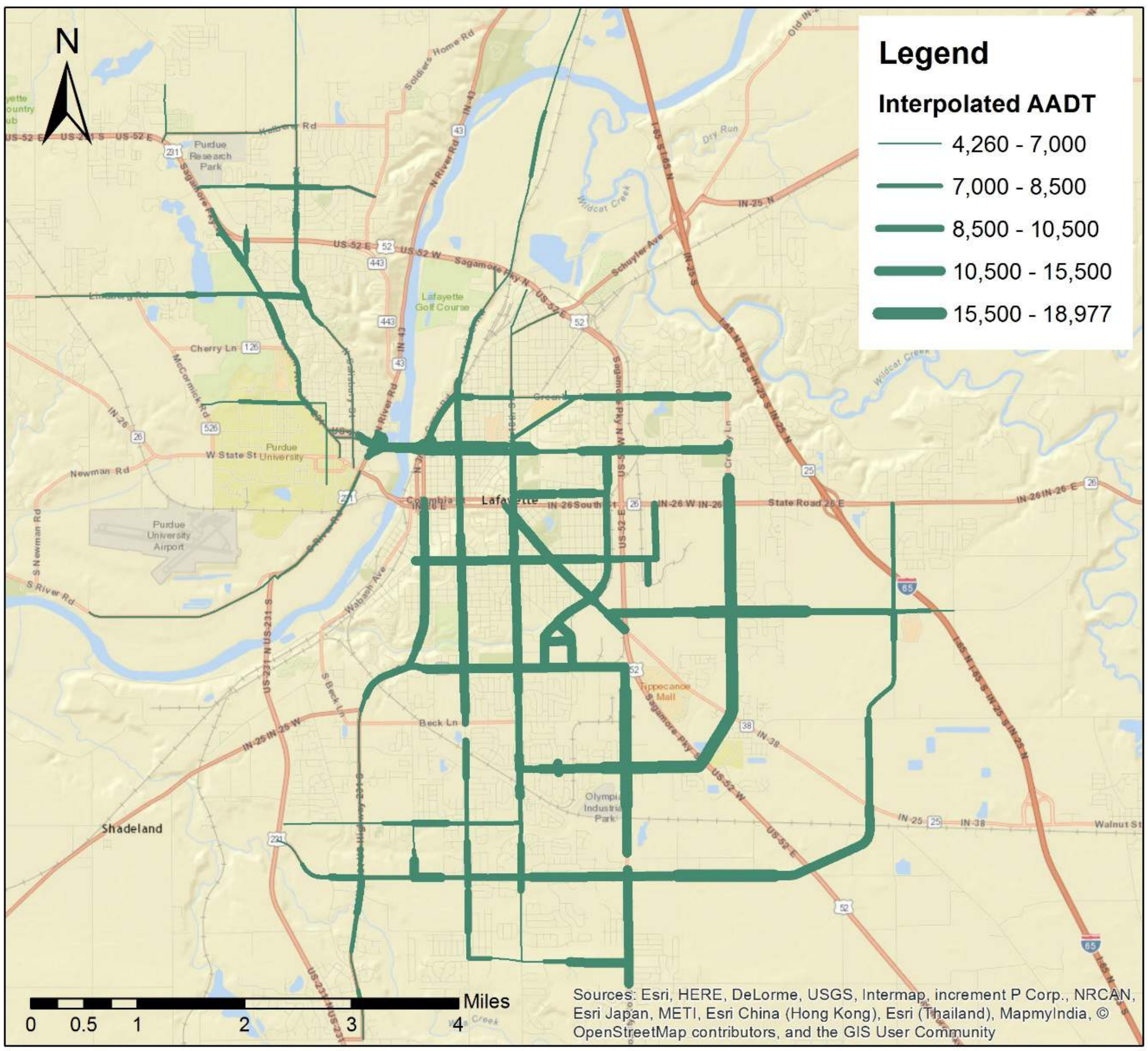

Figure 4.15 Flow map of interpolated traffic for high-volume city streets

Similarly, interpolated VMT for a specific road class, high volume county roads, is presented in Figure 4.16 for Tippecanoe County. These county roads receive traffic from the low volume county roads, and are typically paved routes. The range of interpolated AADT is from 615 to 5,598, with grey shading representing transition areas and high volumes represented by lighter shading. It is expected that high traffic volumes are observed closer to the urban core of Greater Lafayette.

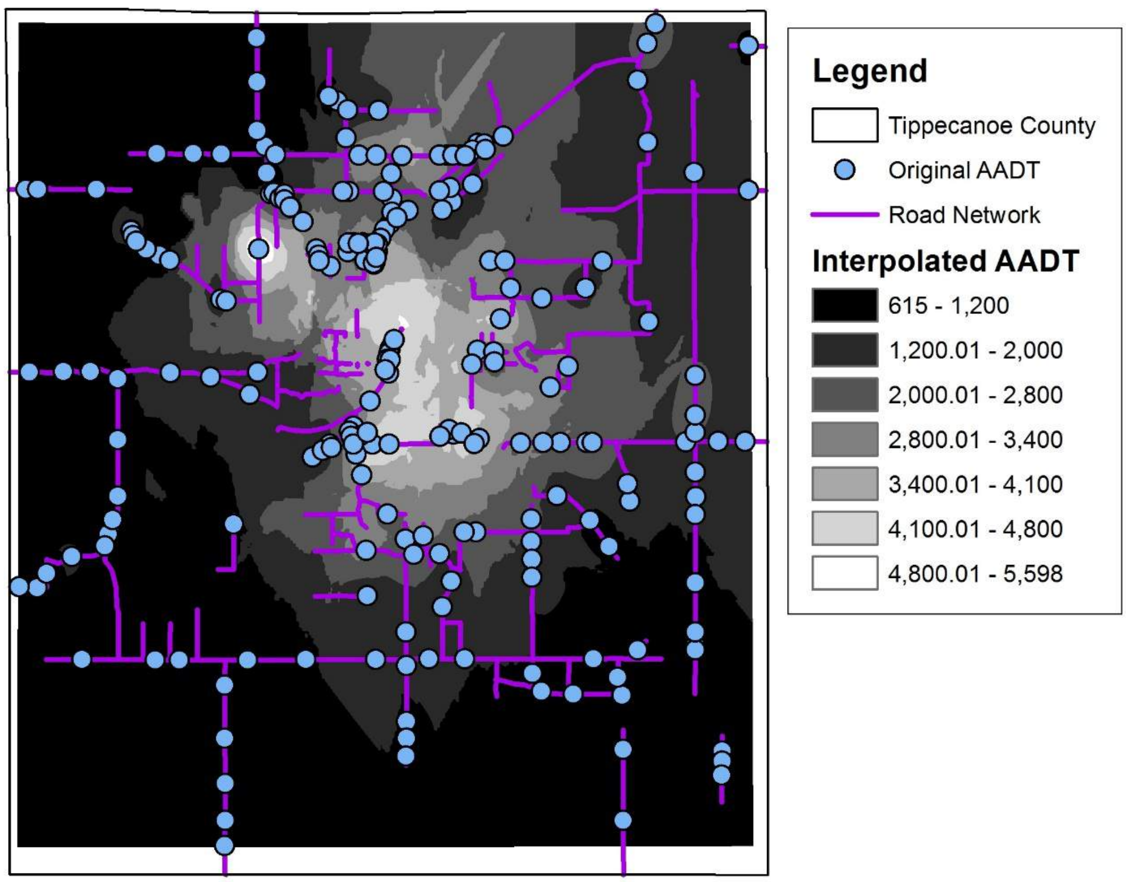

Figure 4.16 Interpolated VMT for high volume county roads (Tippecanoe County)

4.4.4 Segment Level VMT Estimation

Examination of VMT estimates at the segment level reveals significant differences in the predicted VMT. The known traffic attributes, including segment ID, link length, AADT, and daily VMT are provided in Table 4.14 for a sample of road segments; as well as the predicted daily VMT from each spatial interpolation technique. Depending on the local route road class, low and high volume city streets and county roads, the percent difference from the actual VMT varies among techniques. Trend interpolation has the highest deviation, indicating that this technique is not appropriate for local roads when no underlying trend is known or assumed.

Excluding results from the trend technique, high volume city streets have percent differences from -27.47% to -21.97%; low volume city streets range from 9.48% to 6.76%; high volume county roads range from 7.69% to 13.22%; and low volume county roads range from 13.84% to 22.39%.

Table 4.14 Sample county segment level VMT estimation from spatial interpolation

	Known Traffic Attributes				Predicted Daily VMT (Spatial Interpolation)				Percent Difference (Spatial Interpolation)			
Functional Class	**Road Segment ID**	**Link Length (miles)**	**AADT**	**DVMT**	**Kriging**	**IDW**	**Natural Neighbor**	**Trend**	**Kriging**	**IDW**	**Natural Neighbor**	**Trend**
City Streets - High Volume	7558	0.07	18,247	1,258.6	539	528	537	551	-57.21%	-58.08%	-57.31%	-56.23%
City Streets - High Volume	1418	0.41	14,238	5,787.2	2,703	2,666	2,779	3,609	-53.29%	-53.93%	-51.98%	-37.64%
City Streets - High Volume	10425	0.11	12,224	1,311.6	1,178	1,056	1,270	1,316	-10.15%	-19.46%	-3.17%	0.33%
City Streets - High Volume	6246	0.25	10,964	2,775.8	2,113	2,042	1,753	3,032	-23.88%	-26.44%	-36.85%	9.23%
City Streets - High Volume	10,028	0.14	9,624	1,393.3	1,178	1,365	1,376	939	-15.44%	-2.02%	-1.27%	-32.64%
City Streets - High Volume	9509	0.10	7,926	795.1	695	670	825	833	-12.64%	-15.75%	3.81%	4.79%
City Streets - High Volume	8845	0.09	6,566	605.4	590	505	563	692	-2.57%	-16.59%	-7.01%	14.27%
Average Percent Difference									**-25.03%**	**-27.47%**	**-21.97%**	**-13.98%**
City Streets - Low Volume	5044	0.05	439.0	21.9	29.4	25.6	39.6	93.9	34.40%	17.31%	81.32%	329.61%
City Streets - Low Volume	8719	0.06	1,016.0	62.8	56.1	44.8	49.2	117.7	-10.63%	-28.74%	-21.65%	87.40%
City Streets - Low Volume	3446	0.06	2,021.0	128.1	95.6	73.7	70.3	127.9	-25.33%	-42.45%	-45.13%	-0.15%
City Streets - Low Volume	1763	0.10	2,806.0	270.3	209.4	241.8	292.7	246.0	-22.56%	-10.55%	8.27%	-9.02%
City Streets - Low Volume	2841	0.04	4,844.0	182.9	90.0	66.4	90.1	96.7	-50.78%	-63.69%	-50.74%	-47.13%
City Streets - Low Volume	3792	0.05	2,501.0	135.1	118.9	139.9	164.7	138.5	-12.00%	3.56%	21.95%	2.52%
City Streets - Low Volume	2211	0.06	737.0	47.2	73.7	74.6	72.3	156.4	56.31%	58.21%	53.32%	231.48%
Average Percent Difference									**-4.37%**	**-9.48%**	**6.76%**	**84.96%**
County Roads - High Volume	582	0.14	499.0	68.6	126.7	116.6	116.1	220.2	84.57%	69.94%	69.09%	220.79%
County Roads - High Volume	780	0.24	2,504.0	601.7	676.0	710.6	753.4	512.4	12.34%	18.08%	25.20%	-14.85%
County Roads - High Volume	1081	0.33	1,761.0	579.9	657.5	623.9	567.9	822.7	13.38%	7.60%	-2.06%	41.88%
County Roads - High Volume	1185	0.10	1,039.0	102.2	116.5	97.5	98.2	203.1	13.96%	-4.64%	-3.99%	98.64%
County Roads - High Volume	1198	0.25	870.0	219.9	234.7	240.5	242.8	460.2	6.76%	9.36%	10.40%	109.28%
County Roads - High Volume	3434	0.24	1,634.0	394.7	342.5	329.2	269.3	420.7	-13.22%	-16.59%	-31.75%	6.61%
County Roads - High Volume	3849	0.18	1,241.0	220.5	164.8	164.7	191.7	329.2	-25.25%	-25.30%	-13.08%	49.29%
Average Percent Difference									**13.22%**	**8.35%**	**7.69%**	**73.09%**
County Roads - Low Volume	249	1.36	25.0	33.9	81.3	84.1	73.2	164.0	140.00%	148.00%	116.00%	384.00%
County Roads - Low Volume	6660	0.77	40.0	30.7	40.7	44.5	28.4	76.8	32.50%	45.00%	-7.50%	150.00%
County Roads - Low Volume	5678	0.76	86.0	65.2	34.9	37.9	34.9	95.5	-46.51%	-41.86%	-46.51%	46.51%
County Roads - Low Volume	4764	0.53	519.0	276.9	83.2	60.8	109.4	59.8	-69.94%	-78.03%	-60.50%	-78.42%
County Roads - Low Volume	6605	0.28	335.0	92.8	72.3	54.0	72.3	44.6	-22.09%	-41.79%	-22.09%	-51.94%
County Roads - Low Volume	10870	0.26	303.0	79.8	74.5	94.8	109.3	41.6	-6.60%	18.81%	36.96%	-47.85%
County Roads - Low Volume	7700	0.48	272.0	131.4	226.1	271.5	237.2	107.2	72.06%	106.62%	80.51%	-18.38%
Average Percent Difference									**14.20%**	**22.39%**	**13.84%**	**54.84%**

4.4.5 County Level VMT Estimation

Aggregating VMT for all segments of each local road class, a total local VMT is estimated for three representative counties analyzed in this study. The results of these county level aggregate estimates are provided in Table 4.15 to Table 4.17, for Tippecanoe, St. Joseph, and Jefferson County, respectively.

Each spatial interpolation technique assessed in this study produces annual VMT (AVMT) values which are relatively similar to each other. For example, the predicted AVMT for Tippecanoe County is 644.0 to 695.9 million; St. Joseph County is estimated as 1,291 to 1,387 million; and Jefferson County is estimated as 94.8 to 101.6 million. On average, estimates from Kriging are higher and estimates from Natural Neighbor are lower, with relative standing dependent on the county analyzed.

Table 4.15 Total local VMT from spatial interpolation (Tippecanoe County)

		Predicted AVMT			
Functional Class	**Total Length (miles)**	**Kriging**	**IDW**	**Natural Neighbor**	**Trend**
County Roads - High Volume	258.73	182,050,209	176,747,687	178,703,278	196,666,263
County Roads - Low Volume	497.50	33,140,117	31,752,328	35,715,880	28,554,652
City Streets - High Volume	89.81	302,909,260	298,864,673	291,544,077	289,123,522
City Streets - Low Volume	182.45	140,849,296	138,338,070	103,789,575	147,258,658
Neighborhood Roads	469.62	34,282,421			
Total Local Route VMT		**693,231,303**	**679,985,180**	**644,035,231**	**695,885,515**

Table 4.16 Total local VMT from spatial interpolation (Jefferson County)

		Predicted AVMT			
Functional Class	**Total Length (miles)**	**Kriging**	**IDW**	**Natural Neighbor**	**Trend**
County Roads	457.28	44,058,846	42,167,736	38,843,412	45,421,262
City Streets	40.40	37,737,758	36,598,518	36,181,414	33,289,018
Neighborhood Roads	271.27	19,802,969			
Total Local Route VMT		**101,599,573**	**98,569,223**	**94,827,795**	**98,513,250**

Table 4.17 Total local VMT from spatial interpolation (St. Joseph County)

		Predicted AVMT			
Functional Class	**Total Length (miles)**	**Kriging**	**IDW**	**Natural Neighbor**	**Trend**
County Roads - High Volume	138.05	97,221,130	98,430,796	95,095,767	105,738,226
County Roads - Low Volume	516.53	87,530,969	83,911,639	84,131,626	99,657,302
City Streets - High Volume	128.16	517,911,961	494,649,971	483,991,742	526,132,856
City Streets - Low Volume	495.10	592,352,090	576,447,480	608,978,923	617,739,107
Neighborhood Roads	511.46	37,336,666			
Total Local Route VMT		**1,332,352,817**	**1,290,776,552**	**1,309,534,724**	**1,386,604,156**

4.4.6 Validation of the Estimated VMT

These techniques are only as good as their relative accuracy. To gauge the accuracy and extent of suitability associated with each technique, a validation approach is used. To validate these techniques, 90% of the original AADT counts were used for modeling, with 10% of the dataset set aside for validation. The same validation dataset was used for comparing predicted and actual daily VMT. The technique with the lowest root mean square error (RMSE), shown in Equation 4.1, was identified as the best approach. The process was repeated for all techniques and each road class. Here, y_{pred} refers to the interpolated daily VMT, y_{actual} gives the known daily VMT and N is the number of observations in the validation dataset.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_{pred} - y_{actual}\right)^2} \quad \ldots\ldots\ldots\ldots\ldots(4.1)$$

Table 4.18 through Table 4.22 show the validation results by each county and technique, depending on the level of urbanization of the counties. These accuracy tables help to identify the lowest RMSE, or the difference between the predicted and observed VMT values. This establishes the most appropriate spatial interpolation technique to select for a road class, accounting for different degrees of urbanization in a geographical setting. The highlighted values represent the best technique for each road class.

Table 4.18 presents the best technique for the combined road classes without segmentation. The best technique is shown in for low-volume city streets, high-volume city streets, low-volume county roads, and high-volume county roads, respectively.

These results show that the feasibility of spatial interpolation techniques for local route VMT estimation greatly depends on the type of county, rural, mixed, or urban, and road class under investigation.

Table 4.18 Accuracy for all road classes

All Local Routes Road Classes, RMSE		**County**		
		Jefferson	Tippecanoe	St. Joseph
		Rural	Mixed	Urban
Spatial Interpolation Techniques	Kriging	139	557	1431
	Inverse Distance Weighting	92	404	1487
	Natural Neighbor	85	332	788
	Trend	175	1483	1567

Table 4.19 Accuracy for low-volume city streets

City Streets - Low Volume RMSE		**County**		
		Jefferson	Tippecanoe	St. Joseph
		Rural	Mixed	Urban
Spatial Interpolation Techniques	Kriging	42	45	281
	Inverse Distance Weighting	64	51	212
	Natural Neighbor	37	45	205
	Trend	82	63	269

Table 4.20 Accuracy for high-volume city streets

City Streets - High Volume RMSE		**County** Jefferson	Tippecanoe	St. Joseph
		Rural	Mixed	Urban
Spatial Interpolation Techniques	Kriging	N/A	1087	1418
	Inverse Distance Weighting	N/A	1108	1174
	Natural Neighbor	N/A	1101	963
	Trend	N/A	787	1473

Table 4.21 Accuracy for low-volume county roads

County Roads - Low Volume RMSE		**County** Jefferson	Tippecanoe	St. Joseph
		Rural	Mixed	Urban
Spatial Interpolation Techniques	Kriging	78	78	189
	Inverse Distance Weighting	76	83	183
	Natural Neighbor	103	87	136
	Trend	116	88	323

Table 4.22 Accuracy for high-volume county roads

County Roads - High Volume, RMSE		**County** Jefferson	Tippecanoe	St. Joseph
		Rural	Mixed	Urban
Spatial Interpolation Techniques	Kriging	N/A	304	415
	Inverse Distance Weighting	N/A	286	469
	Natural Neighbor	N/A	229	432
	Trend	N/A	648	548

A metropolitan planning organization (MPO) or highway agency may necessitate project level VMT estimates. This research methodology can be applied to estimate local AADT/VMT for individual segments or highway corridors with unavailable traffic counts. The validation process of this section enables the selection of the most appropriate spatial interpolation technique, depending on the road class.

Example AADT maps for Tippecanoe County, Indiana, produced in ArcGIS using the most appropriate spatial interpolation technique (based on the validation process results) are provided in Appendix B. Using different techniques to develop each road class layer is expected to be of higher accuracy and reliability, than producing one map for the entire county.

Depending on the end-user needs, such as VMT estimation for a corridor or specific highway segment, the maps (applicable for local routes) in Figure B.1 for county roads, to Figure B.2, for city streets, represent the capability to obtain traffic volumes and estimate local VMT for any section of the local road network.

4.5 Non-Traffic VMT Estimation Methods

This section provides additional intermediate inputs for non-traffic methods of VMT estimation such as fuel, regression, and travel surveys.

4.5.1 Intermediate Inputs

Fleet fuel efficiencies are weighted for each year of analysis. Table 4.23 gives fuel efficiencies for gasoline (top row) and diesel (bottom row) vehicles, by approach. The average ranges from 21.59 to 21.88 MPG for vehicle class 1 to 3 (which mostly used gasoline) and 6.51 to 7.54 MPG for vehicle classes 4 to 13 (which mostly used diesel).

Table 4.23 Weighted fuel efficiencies by approach

Approach	2009	2010	2011	2012
Estimated fuel revenues (disaggregate, link-level)	21.61 6.78	21.45 6.68	21.63 7.99	21.38 6.90
Estimated fuel revenues (aggregate, FHWA)	22.13 6.62	22.13 6.62	22.14 6.65	21.73 6.21
Reported fuel consumed (aggregate, link-level)	21.86 7.57	21.86 7.57	21.85 7.96	21.67 6.43
Average for Fuel Method	21.87 6.99	21.81 6.96	21.88 7.54	21.59 6.51

The traffic distributions used for statewide estimation are weighted between state and local routes. These vehicle class distributions are given in Table 4.24. As observed, Class 2 (automobiles), Class 3 (primarily light-duty trucks and SUVs), and Class 9 (heavy trucks) constitute the majority of the traffic stream, with 62.67%, 24.98%, and 5.95%, respectively for 2013.

Table 4.24 Weighted average traffic for statewide estimation

Vehicle Classes	2009	2010	2011	2012	2013
Class 1	0.54%	0.54%	0.55%	0.55%	0.55%
Class 2	61.80%	61.86%	63.72%	62.67%	62.67%
Class 3	24.73%	24.74%	25.63%	24.98%	24.98%
Class 4	0.19%	0.19%	0.16%	0.22%	0.22%
Class 5	2.40%	2.38%	2.28%	3.02%	3.02%
Class 6	0.76%	0.76%	1.01%	1.28%	1.28%
Class 7	0.23%	0.23%	0.32%	0.41%	0.41%
Class 8	0.80%	0.80%	0.56%	0.60%	0.60%
Class 9	8.14%	8.09%	5.49%	5.95%	5.95%
Class 10	0.12%	0.12%	0.08%	0.09%	0.09%
Class 11	0.18%	0.18%	0.12%	0.14%	0.14%
Class 12	0.06%	0.06%	0.04%	0.05%	0.05%
Class 13	0.04%	0.04%	0.03%	0.03%	0.03%

Based on socioeconomic travel surveys, personal VMT (classes 1 to 3) is estimated by land-area groups shown in Figure 4.17. Dense Urban, Light Urban, and Rural represent all possible household locations. Based on reported household incomes, VMT is highest for dense urban, light urban, and rural, respectively, for household incomes of \$20K-\$40K; greater than \$100K, and \$40K-\$60K.

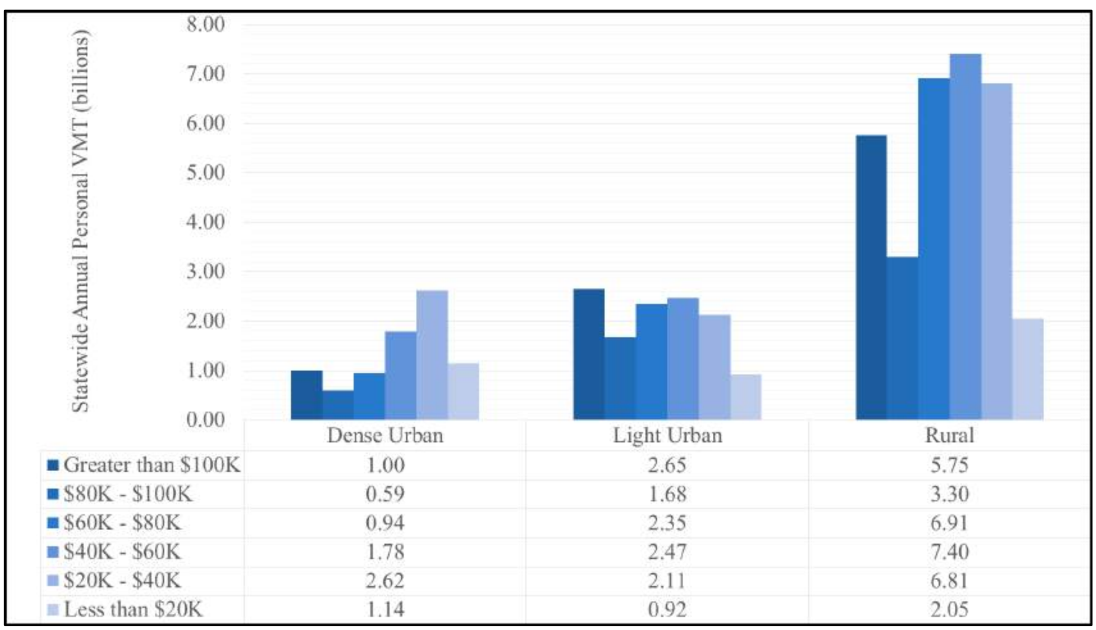

Figure 4.17 Personal VMT by income and land-area groups

For example, from travel surveys, the distribution of personal VMT for dense-urban households is shown by Figure 4.18. Household incomes of $20K-$40K and $40-60K constitute a combined 55% of the total VMT for this type of household location in Indiana cities (Indianapolis, Fort Wayne etc.).

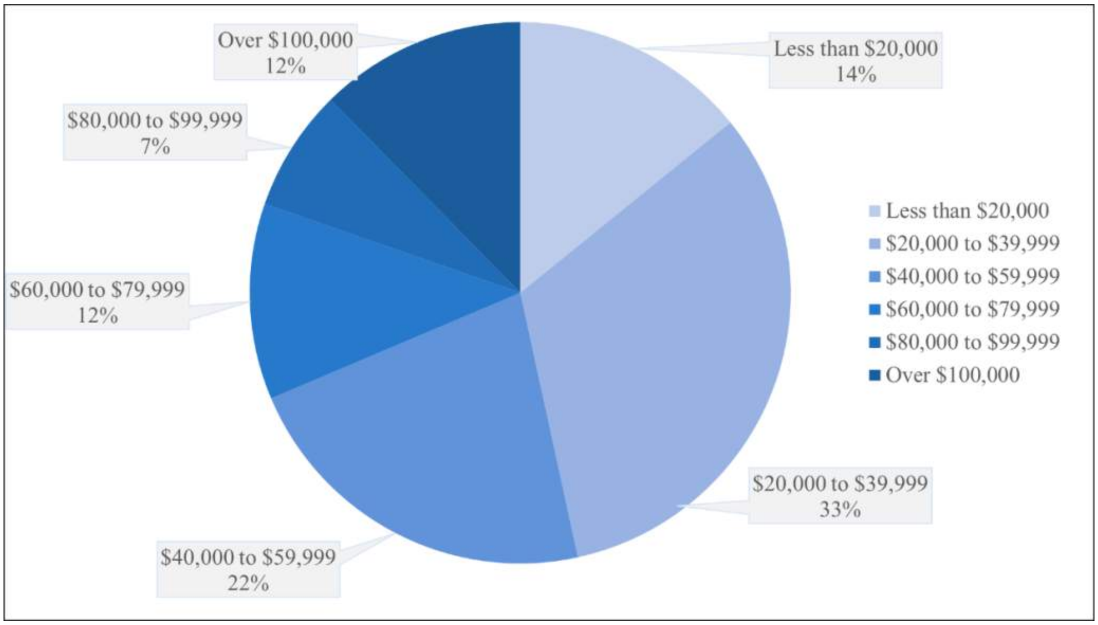

Figure 4.18 Distribution of personal VMT for dense-urban households

4.5.2 Trend Analysis

This section provides the models investigated to predict VMT based on trend analysis. These functional forms differ greatly with respect to accuracy and predictive capabilities. Linear, polynomial, s-curve model, growth curve, and annual growth factors were investigated. The equations for the functional forms are given in Figure 4.19, for s-curve model, Figure 4.20 for growth curve model, and Figure 4.21 for linear trend. Index one represents 1992, the first year with historical statewide VMT data available. Index 18 represents 2009, the first year for predicted statewide VMT. The s-curve predicts the same VMT of around 74 billion in 2015, the growth curve predicts a VMT of around 85 billion in 2015, and the linear curve also predicts a VMT of around 85 billion in 2015.

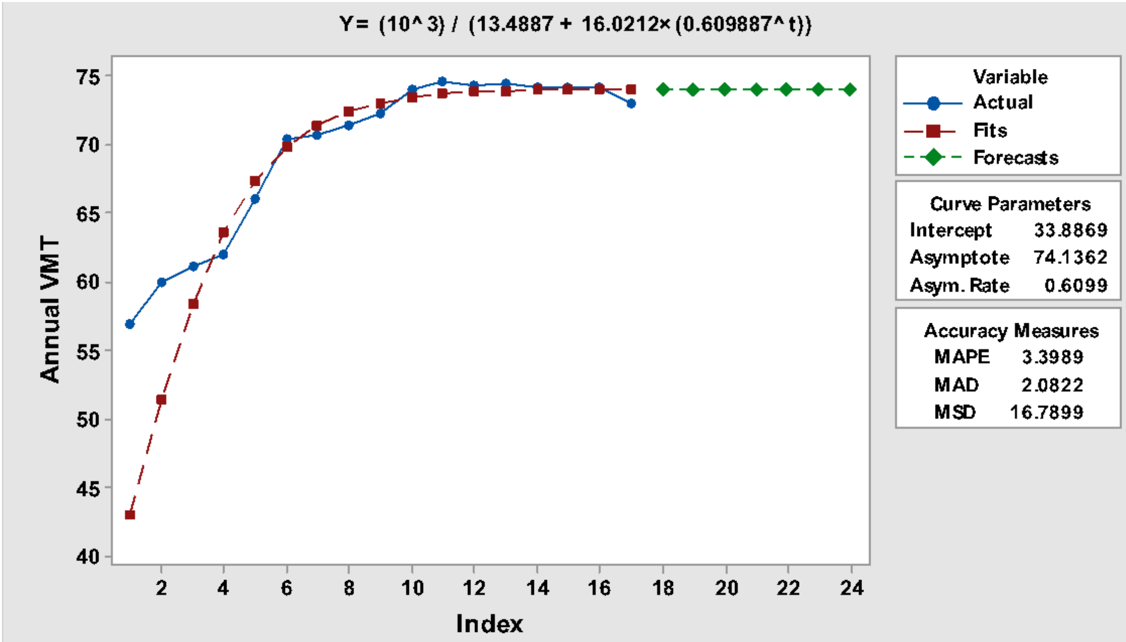

Figure 4.19 S-curve trend model for annual VMT prediction

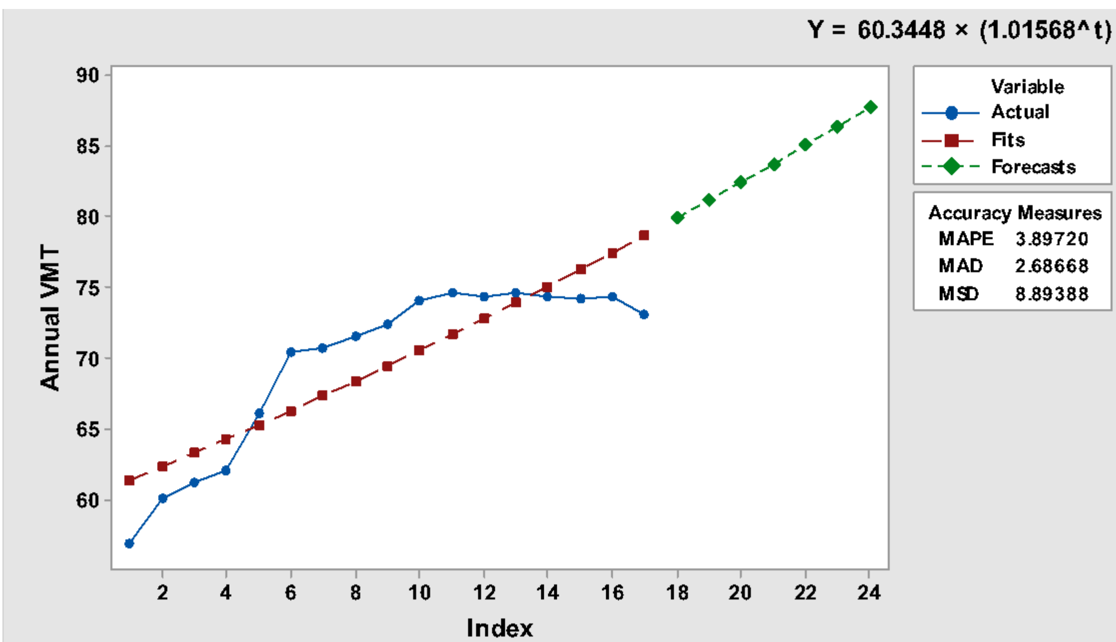

Figure 4.20 Growth curve model for annual VMT prediction

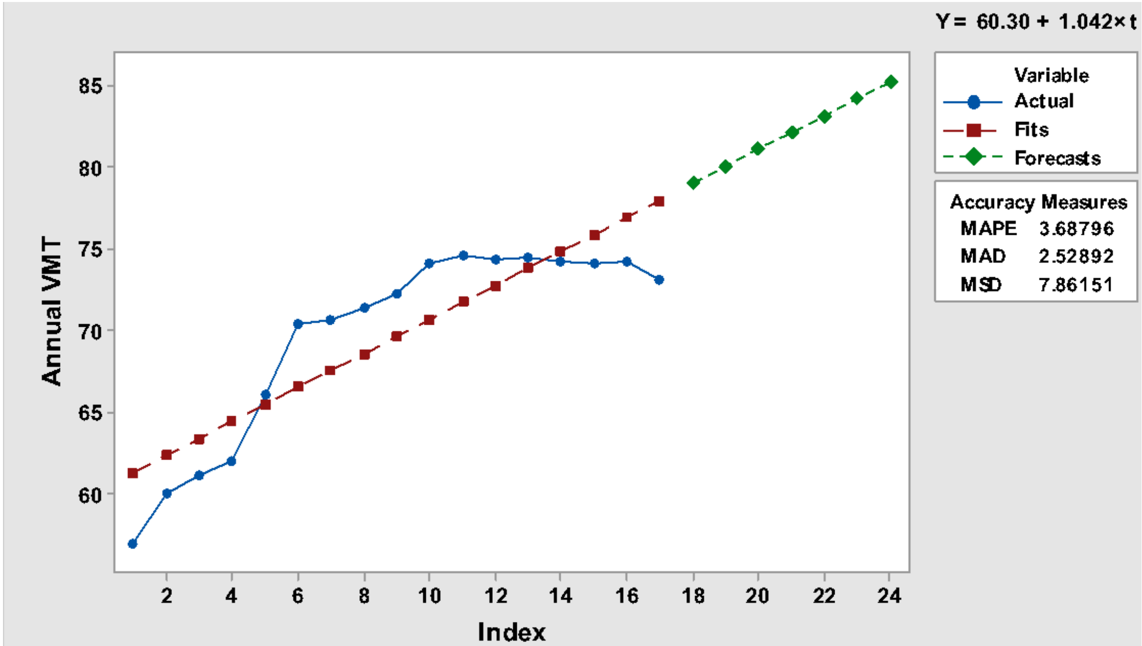

Figure 4.21 Linear trend model for annual VMT prediction

The extent of prediction error from the actual, VMT from literature (INDOT, 2013) is provided in Table 4.25. As observed, the linear trend model consistently overestimated the VMT; whereas, the polynomial trend model underestimated for 2009 and progressively overestimated the VMT for the remaining analysis years. The S-curve trend model underestimated the VMT for all years except 2010. Finally, growth factors underestimated the VMT for 2009 and there was a small overestimate in 2010 to 2013. These findings indicate that the predictive capabilities of various techniques of trend analysis and growth factors greatly influence the accuracy and thus the results obtained.

Table 4.25 Extent of prediction error by trend analysis technique

Analysis Years	Linear Trend	Polynomial Trend	Growth Curve Model	S-Curve Trend	Growth Factors
2009	2.0%	-6.9%	3.0%	-4.4%	-3.8%
2010	10.7%	4.0%	12.1%	2.4%	5.2%
2011	4.8%	1.0%	6.3%	-4.3%	0.3%
2012	4.5%	3.4%	6.4%	-5.7%	0.8%
2013	4.9%	6.3%	7.1%	-6.6%	1.9%

4.6 Chapter Summary

This chapter built upon the framework of Chapter 3 to provide the technical analysis and modeling for statewide VMT estimation for both local and state routes. To implement this framework and provide a platform for future use, a traffic count database was created. This database contains extensive link-level (highway segment) traffic count data, which were used for estimation and prediction of traffic volumes and consequently VMT estimates. In order to increase the reliability and consistency of local VMT estimates, the local VMT estimation approach was discussed in detail.

A GIS platform was implemented to estimate the segment lengths, analyze the traffic count sample, more accurately estimate VMT using representative counties throughout the state, and create local road classes. To expand the traffic count sample used for local VMT estimation to the entire state of Indiana, cluster analysis was used to group counties, using VMT-related characteristics such as urban population, commute times, and vehicle registrations.

Applications of spatial interpolation for local VMT estimation were presented, using existing traffic counts to estimate VMT by road class within a county. The techniques, implementation for Indiana, and the accuracy of each technique were discussed.

Finally, analysis of the inputs and intermediate steps for non-traffic methods of VMT estimation were conducted, with emphasis on inputs and intermediate steps for the fuel-revenue and trend analysis methods.

CHAPTER 5. RESULTS AND DISCUSSION

5.1 Estimated Statewide VMT (Link-Level)

This section contains Indiana statewide VMT estimates, aggregated from the segment level using a comprehensive traffic database. These aggregated results represent the annual VMT, which is provided for varying scopes and users including the county-level, administrative district, road designation, economic region, and comparison to the HPMS. These aggregations assist policymakers with assessing the existing VMT conditions, as well as providing long-term predictions for applications necessitating VMT.

5.1.1 Aggregation by County

The local route VMT was based on data applicable for 2013 but is expected to be transferable to prior years because of the limited variation observed in growth rates. A summary of the county-wide VMT is shown in Table 5.1 and Table 5.2 for state and local routes, respectively. The statewide total represents each county's annual contribution to the statewide VMT. For example, Elkhart County had a VMT of 591.60 million on state routes and 855.94 million on local routes, for a county-wide total of 1447.54 million. Note that the state routes and statewide total are for mainline segments and do not include ramps as they account for minimal VMT. Similarly, the percentage of VMT of local and state routes represent the proportion of travel that occurs on these road types. For example, Allen County had 61.65% and 38.35% on local and state routes, respectively, indicating that more VMT was attributed to local roads. Counties which do not have interstates and other high-volume roads may observe a higher proportion of their total VMT from local routes.

Table 5.1 Summary of state and local VMT by county

County ID	County Name	State Route Average (millions)	Local Route Average (millions)	Total (millions)	Local Route (%)	State Route (%)
01	Adams	161.62	154.00	315.62	48.79%	51.21%
02	Allen	1539.96	2475.79	4015.75	61.65%	38.35%
03	Bartholomew	772.34	407.57	1179.90	34.54%	65.46%
04	Benton	66.82	141.65	208.47	67.95%	32.05%
05	Blackford	53.10	75.44	128.55	58.69%	41.31%
06	Boone	761.86	407.77	1169.63	34.86%	65.14%
07	Brown	74.67	78.04	152.71	51.10%	48.90%
08	Carroll	140.71	158.39	299.10	52.95%	47.05%
09	Cass	164.08	195.66	359.73	54.39%	45.61%
10	Clark	644.75	550.70	1195.45	46.07%	53.93%
11	Clay	278.37	145.49	423.86	34.32%	65.68%
12	Clinton	341.53	170.00	511.53	33.23%	66.77%
13	Crawford	199.01	93.86	292.87	32.05%	67.95%
14	Daviess	167.51	176.86	344.37	51.36%	48.64%
15	Dearborn	434.79	244.90	679.68	36.03%	63.97%
16	Decatur	257.46	143.85	401.31	35.84%	64.16%
17	Dekalb	362.99	169.34	532.33	31.81%	68.19%
18	Delaware	573.51	816.73	1390.24	58.75%	41.25%
19	Dubois	248.49	349.75	598.24	58.46%	41.54%
20	Elkhart	591.60	855.94	1447.54	59.13%	40.87%
21	Fayette	83.11	238.80	321.91	74.18%	25.82%
22	Floyd	407.57	223.24	630.81	35.39%	64.61%
23	Fountain	172.55	144.74	317.28	45.62%	54.38%
24	Franklin	131.69	129.75	261.45	49.63%	50.37%
25	Fulton	129.69	164.71	294.40	55.95%	44.05%
26	Gibson	349.83	213.99	563.81	37.95%	62.05%
27	Grant	492.10	456.35	948.45	48.11%	51.89%
28	Greene	218.21	191.59	409.79	46.75%	53.25%
29	Hamilton	1256.76	1746.06	3002.82	58.15%	41.85%
30	Hancock	583.17	358.48	941.65	38.07%	61.93%
31	Harrison	350.92	170.75	521.66	32.73%	67.27%
32	Hendricks	764.59	778.17	1542.76	50.44%	49.56%
33	Henry	477.01	183.57	660.58	27.79%	72.21%
34	Howard	256.24	386.28	642.52	60.12%	39.88%
35	Huntington	447.54	156.95	604.49	25.96%	74.04%
36	Jackson	543.18	169.11	712.29	23.74%	76.26%
37	Jasper	574.11	199.36	773.47	25.77%	74.23%
38	Jay	121.80	161.53	283.32	57.01%	42.99%
39	Jefferson	183.24	121.54	304.79	39.88%	60.12%
40	Jennings	166.22	139.05	305.28	45.55%	54.45%
41	Johnson	757.92	654.88	1412.80	46.35%	53.65%
42	Knox	265.27	206.28	471.54	43.74%	56.26%
43	Kosciusko	367.10	575.75	942.86	61.06%	38.94%
44	LaGrange	174.13	161.42	335.55	48.11%	51.89%
45	Lake	2625.88	2076.30	4702.18	44.16%	55.84%
46	LaPorte	737.33	912.73	1650.06	55.31%	44.69%

Table 5.2 Summary of state and local VMT by county (continued)

County ID	County Name	State Route Average (millions)	Local Route Average (millions)	Total (millions)	Local Route (%)	State Route (%)
47	Lawrence	248.69	156.74	405.43	38.66%	61.34%
48	Madison	669.91	925.38	1595.29	58.01%	41.99%
49	Marion	4227.24	5156.55	9383.79	54.95%	45.05%
50	Marshall	349.61	204.55	554.17	36.91%	63.09%
51	Martin	93.65	79.40	173.06	45.88%	54.12%
52	Miami	237.61	171.68	409.29	41.95%	58.05%
53	Monroe	462.06	631.11	1093.17	57.73%	42.27%
54	Montgomery	326.89	183.26	510.15	35.92%	64.08%
55	Morgan	524.86	342.83	867.69	39.51%	60.49%
56	Newton	170.03	138.14	308.18	44.83%	55.17%
57	Noble	247.81	182.64	430.45	42.43%	57.57%
58	Ohio	26.42	28.77	55.19	52.13%	47.87%
59	Orange	122.87	130.30	253.18	51.47%	48.53%
60	Owen	119.23	127.68	246.91	51.71%	48.29%
61	Parke	94.69	153.73	248.42	61.88%	38.12%
62	Perry	152.10	108.36	260.46	41.60%	58.40%
63	Pike	117.29	112.82	230.10	49.03%	50.97%
64	Porter	985.21	700.06	1685.27	41.54%	58.46%
65	Posey	216.84	152.23	369.07	41.25%	58.75%
66	Pulaski	84.25	179.14	263.39	68.01%	31.99%
67	Putnam	419.18	164.73	583.91	28.21%	71.79%
68	Randolph	124.88	185.02	309.90	59.70%	40.30%
69	Ripley	258.17	154.17	412.34	37.39%	62.61%
70	Rush	108.04	156.36	264.40	59.14%	40.86%
71	St. Joseph	707.47	1745.29	2452.76	71.16%	28.84%
72	Scott	245.90	71.80	317.70	22.60%	77.40%
73	Shelby	451.60	184.77	636.37	29.03%	70.97%
74	Spencer	242.63	157.85	400.47	39.42%	60.58%
75	Starke	157.09	142.53	299.62	47.57%	52.43%
76	Steuben	288.94	139.76	428.70	32.60%	67.40%
77	Sullivan	147.19	187.82	335.01	56.06%	43.94%
78	Switzerland	57.39	72.38	129.76	55.78%	44.22%
79	Tippecanoe	808.02	684.77	1492.79	45.87%	54.13%
80	Tipton	170.21	119.02	289.23	41.15%	58.85%
81	Union	46.34	55.31	101.65	54.41%	45.59%
82	Vanderburgh	716.99	597.63	1314.62	45.46%	54.54%
83	Vermillion	172.52	93.57	266.09	35.16%	64.84%
84	Vigo	525.70	786.86	1312.57	59.95%	40.05%
85	Wabash	188.68	164.27	352.95	46.54%	53.46%
86	Warren	85.51	112.91	198.42	56.90%	43.10%
87	Warrick	353.12	353.60	706.72	50.03%	49.97%
88	Washington	144.63	163.32	307.94	53.03%	46.97%
89	Wayne	529.96	636.39	1166.34	54.56%	45.44%
90	Wells	137.41	154.59	291.99	52.94%	47.06%
91	White	326.85	195.20	522.05	37.39%	62.61%
92	Whitley	289.86	135.76	425.62	31.90%	68.10%

For local routes, the county cluster group for statewide expansion, local routes centerline mileage, adjusted annual VMT, study VMT, reported VMT, and percent difference between study and reported, are shown in Table 5.3 and Table 5.4, respectively. The units of the study and VMT from the past literature are in millions. The percent differences were primarily between +/- 30%. Counties with percent differences of greater than +/-30% may be result from the nature of the cluster assignment and the availability of traffic data. For example, counties are heterogeneous with varying degrees of urbanization, affecting the assignment of counties and average VMT.

Table 5.3 Summary of local routes county-wide VMT estimates

County Code	County Name	Cluster Group	Local Routes Mileage	% Total as Local Mileage	Adjusted VMT per Mile	Study Annual VMT (millions)	Reported Annual VMT (millions)	% Difference
1	Adams	8	789.2	88.7	195,124	154.00	143.81	-6.6%
2	Allen	4	2571.4	90.9	962,818	2475.79	3043.74	22.9%
3	Bartholomew	7	975.8	82.6	417,681	407.57	468.30	14.9%
4	Benton	8	725.9	86.8	195,124	141.65	88.33	-37.6%
5	Blackford	8	386.7	89.9	195,124	75.44	98.55	30.6%
6	Boone	7	976.3	85.2	417,681	407.77	390.92	-4.1%
7	Brown	8	400.0	87.5	195,124	78.04	62.78	-19.6%
8	Carroll	8	811.7	88.0	195,124	158.39	117.53	-25.8%
9	Cass	8	1002.7	88.2	195,124	195.66	263.90	34.9%
10	Clark	6	846.8	75.5	650,350	550.70	496.40	-9.9%
11	Clay	8	745.6	85.8	195,124	145.49	137.97	-5.2%
12	Clinton	8	871.2	87.0	195,124	170.00	141.26	-16.9%
13	Crawford	8	481.1	79.0	195,124	93.86	56.58	-39.7%
14	Daviess	8	906.4	87.9	195,124	176.86	174.47	-1.4%
15	Dearborn	7	586.3	82.5	417,681	244.90	206.23	-15.8%
16	Decatur	8	737.2	89.4	195,124	143.85	178.85	24.3%
17	Dekalb	8	867.8	87.7	195,124	169.34	239.44	41.4%
18	Delaware	6	1255.8	90.3	650,350	816.73	672.33	-17.7%
19	Dubois	7	837.4	85.6	417,681	349.75	198.56	-43.2%
20	Elkhart	5	1602.5	90.2	534,111	855.94	1060.69	23.9%
21	Fayette	5	447.1	92.2	534,111	238.80	107.31	-55.1%
22	Floyd	7	534.5	89.3	417,681	223.24	352.23	57.8%
23	Fountain	8	741.8	84.1	195,124	144.74	94.54	-34.7%
24	Franklin	8	665.0	85.3	195,124	129.75	116.07	-10.5%
25	Fulton	8	844.1	89.4	195,124	164.71	131.04	-20.4%
26	Gibson	8	1096.7	86.4	195,124	213.99	173.74	-18.8%
27	Grant	7	1092.6	87.0	417,681	456.35	351.13	-23.1%
28	Greene	8	981.9	83.8	195,124	191.59	158.78	-17.1%
29	Hamilton	3	1871.9	93.3	932,755	1746.06	2245.12	28.6%
30	Hancock	7	858.3	89.5	417,681	358.48	488.37	36.2%
31	Harrison	8	875.1	84.1	195,124	170.75	121.55	-28.8%
32	Hendricks	6	1196.5	87,7	650,350	778.17	1011.42	30.0%
33	Henry	8	940.8	86.9	195,124	183.57	192.72	5.0%
34	Howard	7	924.8	90.4	417,681	386.28	512.83	32.8%
35	Huntington	8	804.3	79.6	195,124	156.95	185.06	17.9%
36	Jackson	8	866.7	81.9	195,124	169.11	188.34	11.4%
37	Jasper	8	1021.7	85.4	195,124	199.36	212.07	6.4%
38	Jay	8	827.8	89.7	195,124	161.53	142.35	-11.9%
39	Jefferson	8	622.9	73.5	195,124	121.54	143.08	17.7%
40	Jennings	8	712.6	87.9	195,124	139.05	183.60	32.0%
41	Johnson	6	1007.0	87.8	650,350	654.88	840.23	28.3%
42	Knox	8	1057.2	87.5	195,124	206.28	233.97	13.4%
43	Kosciusko	7	1378.5	90.8	417,681	575.75	383.98	-33.3%
44	LaGrange	8	827.3	89.8	195,124	161.42	128.48	-20.4%
45	Lake	2	2503.0	89.3	829,542	2076.30	2706.84	30.4%
46	LaPorte	6	1403.4	86.6	650,350	912.73	512.83	-43.8%

Table 5.4 Summary of local routes county-wide VMT estimates (continued)

County Code	County Name	Cluster Group	Local Routes Mileage	% Total as Local Mileage	Adjusted VMT per Mile	Study Annual VMT (millions)	Reported Annual VMT (millions)	% Difference
47	Lawrence	8	803.3	86.2	195,124	156.74	161.70	3.2%
48	Madison	6	1422.9	89.5	650,350	925.38	782.20	-15.5%
49	Marion	1	3579.0	92.7	1,440,792	5156.55	6240.04	21.0%
50	Marshall	8	1048.3	86.1	195,124	204.55	223.02	9.0%
51	Martin	8	406.9	43.1	195,124	79.40	41.98	-47.1%
52	Miami	8	879.9	86.6	195,124	171.68	188.71	9.9%
53	Monroe	6	970.4	88.6	650,350	631.11	552.25	-12.5%
54	Montgomery	8	939.2	85.2	195,124	183.26	167.17	-8.8%
55	Morgan	7	820.8	85.9	417,681	342.83	404.06	17.9%
56	Newton	8	708.0	85.2	195,124	138.14	87.24	-36.9%
57	Noble	8	936.0	89.2	195,124	182.64	171.55	-6.1%
58	Ohio	8	147.5	84.0	195,124	28.77	20.81	-27.7%
59	Orange	8	667.8	84.8	195,124	130.30	82.13	-37.0%
60	Owen	8	654.4	88.1	195,124	127.68	90.89	-28.8%
61	Parke	8	787.9	89.1	195,124	153.73	133.59	-13.1%
62	Perry	8	555.4	76.7	195,124	108.36	94.90	-12.4%
63	Pike	8	578.2	81.8	195,124	112.82	64.97	-42.4%
64	Porter	5	1310.7	87.4	534,111	700.06	921.99	31.7%
65	Posey	8	780.2	87.8	195,124	152.23	128.48	-15.6%
66	Pulaski	8	918.1	90.7	195,124	179.14	118.26	-34.0%
67	Putnam	8	844.2	85.8	195,124	164.73	163.89	-0.5%
68	Randolph	8	948.2	87.9	195,124	185.02	146.73	-20.7%
69	Ripley	8	790.1	78.6	195,124	154.17	121.91	-20.9%
70	Rush	8	801.3	90.7	195,124	156.36	121.55	-22.3%
71	Scott	8	368.0	81.2	195,124	71.80	86.87	21.0%
72	Shelby	8	946.9	90.6	195,124	184.77	256.23	38.7%
73	Spencer	8	809.0	83.3	195,124	157.85	119.36	-24.4%
74	St. Joseph	3	1871.1	92.1	932,755	1745.29	1965.53	12.6%
75	Starke	8	730.5	87.4	195,124	142.53	95.27	-33.2%
76	Steuben	8	716.3	85.8	195,124	139.76	192.72	37.9%
77	Sullivan	8	962.6	90.0	195,124	187.82	126.29	-32.8%
78	Switzerland	8	370.9	80.9	195,124	72.38	47.82	-33.9%
79	Tippecanoe	5	1282.1	88.3	534,111	684.77	866.51	26.5%
80	Tipton	8	610.0	90.8	195,124	119.02	104.76	-12.0%
81	Union	8	283.5	84.0	195,124	55.31	36.87	-33.4%
82	Vanderburgh	5	1118.9	90.2	534,111	597.63	970.54	62.4%
83	Vermillion	8	479.5	73.7	195,124	93.57	83.95	-10.3%
84	Vigo	6	1209.9	89.7	650,350	786.86	690.58	-12.2%
85	Wabash	8	841.9	85.3	195,124	164.27	145.27	-11.6%
86	Warren	8	578.7	84.9	195,124	112.91	81.40	-27.9%
87	Warrick	7	846.6	85.9	417,681	353.60	297.84	-15.8%
88	Washington	8	837.0	87.8	195,124	163.32	172.65	5.7%
89	Wayne	6	978.5	86.6	650,350	636.39	279.96	-56.0%
90	Wells	8	792.3	88.5	195,124	154.59	137.61	-11.0%
91	White	8	1000.4	87.7	195,124	195.20	191.63	-1.8%
92	Whitley	8	695.8	83.8	195,124	135.76	170.46	25.6%

5.1.2 Aggregation by District and Road Designation

This section provides the VMT aggregated to the six INDOT administrative districts and road designations of interstate, state, and US roads. The districts include Crawfordsville, Greenfield, Vincennes, Fort Wayne, Seymour, and LaPorte. The amount of VMT, in terms of NHS and commercial, is shown in Table 5.5 in million units and is applicable for 2011.

The variation in VMT distribution across districts is evident in Figure 5.1. The Crawfordsville, Greenfield, and LaPorte districts had the highest VMT from interstates. The Greenfield district had the highest interstate VMT of 6,995 million; the Seymour district had the highest VMT from state highways at 2,801 million; and the LaPorte district had the highest VMT from US highways at 2,646 million.

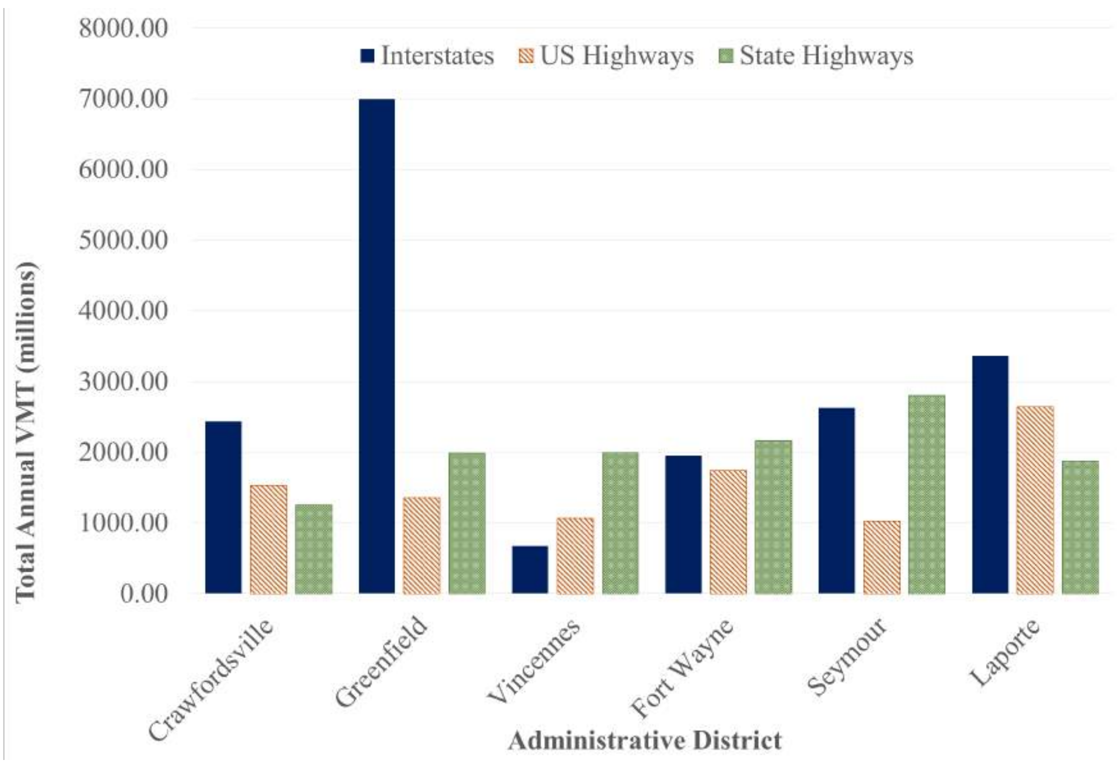

Figure 5.1 Proportion of state route VMT by INDOT administrative district

Table 5.5 State route VMT aggregation by INDOT administrative district

Annual State Route VMT by Administrative District (millions)						
Crawfordsville	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	2439.46	46.71%	2439.46	63.59%	517.99	70.11%
US Highways	1530.54	29.30%	946.65	24.68%	113.53	15.37%
State Highways	1253.04	23.99%	450.12	11.73%	107.33	14.53%
Total	**5223.05**		**3836.23**		**738.85**	
Greenfield	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	6994.81	67.62%	6994.81	75.82%	1171.66	82.00%
US Highways	1359.17	13.14%	1097.29	11.89%	108.60	7.60%
State Highways	1989.76	19.24%	1133.28	12.28%	148.52	10.39%
Total	**10343.75**		**9225.38**		**1428.79**	
Vincennes	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	674.72	18.08%	674.72	25.52%	144.85	33.77%
US Highways	1064.31	28.52%	1042.28	39.42%	122.73	28.61%
State Highways	1992.87	53.40%	927.00	35.06%	161.38	37.62%
Total	**3731.89**		**2644.00**		**428.95**	
Fort Wayne	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	1952.99	33.36%	1952.99	48.53%	367.08	46.34%
US Highways	1738.55	29.70%	1433.69	35.63%	231.16	29.18%
State Highways	2162.59	36.94%	637.53	15.84%	193.83	24.47%
Total	**5854.13**		**4024.21**		**792.07**	
Seymour	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	2627.00	40.72%	2627.00	55.83%	462.65	61.73%
US Highways	1023.04	15.86%	726.17	15.43%	84.38	11.26%
State Highways	2801.30	43.42%	1351.80	28.73%	202.40	27.01%
Total	**6451.35**		**4704.97**		**749.43**	
Laporte	Total	Total (%)	NHS	NHS (%)	Commercial	Comm. (%)
Interstates	3368.53	42.69%	3368.53	52.44%	622.98	54.47%
US Highways	2645.69	33.53%	2139.75	33.31%	350.98	30.69%
State Highways	1875.87	23.78%	915.84	14.26%	169.77	14.84%
Total	**7890.10**		**6424.12**		**1143.73**	

The proportion of commercial VMT by INDOT district is shown in Figure 5.2. The Greenfield district had the highest percentage, at 27.05, with the LaPorte district having the next highest percentage at 21.65. The Vincennes and Seymour districts had the lowest commercial VMT for 2011, with similar trends observed for other analysis years. The proportion of VMT attributed to NHS routes is shown in Figure 5.3. Again, the same observations as the commerical VMT were true, with Greenfield contianing the most VMT on NHS routes, which was heavily influenced by the major interstates located in metropolitan Indianapolis. Similarly, Vincennes in Southern Indiana does not contain as many major interstates which are fully-NHS designated.

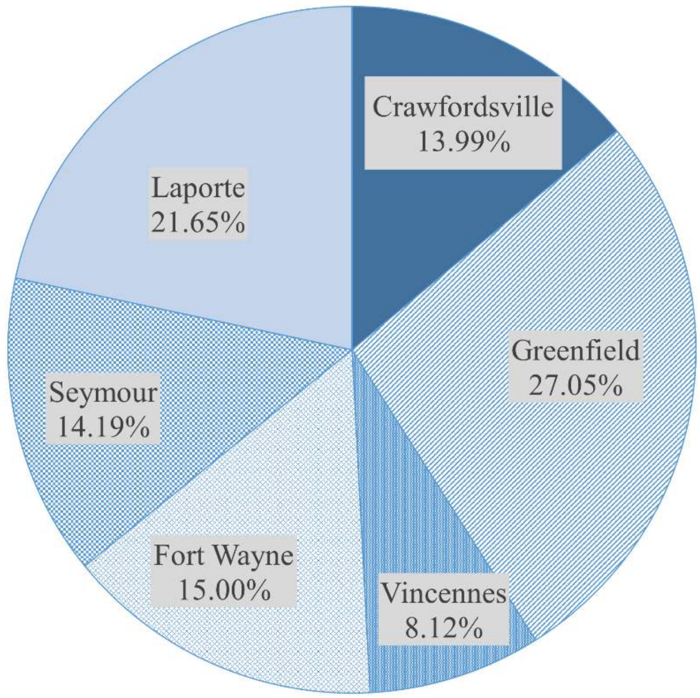

Figure 5.2 Proportion of Commercial VMT by INDOT administrative district

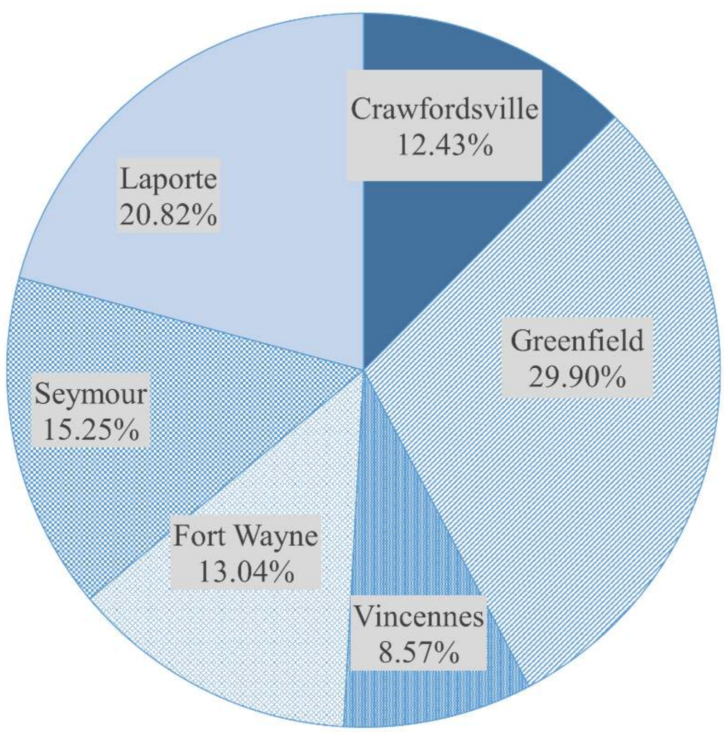

Figure 5.3 Proportion of NHS VMT by INDOT administrative district

5.1.3 Aggregation by Economic Region

Groups of similar counties, notated as economic growth regions (EGR) are another means to analyze VMT. The 12 EGRs defined by the Indiana Department of Workforce Development (IDWD) are referenced in Figure 5.4 (IDWD, 2011). Marion County is its own region, EGR 12. Many counties which comprise the greater Indianapolis metropolitan area, such as Hamilton (Carmel) and Boone (Zionsville) are part of EGR5. The link-level database has an indicator to assign each network link to the county and EGR inn which it is located.

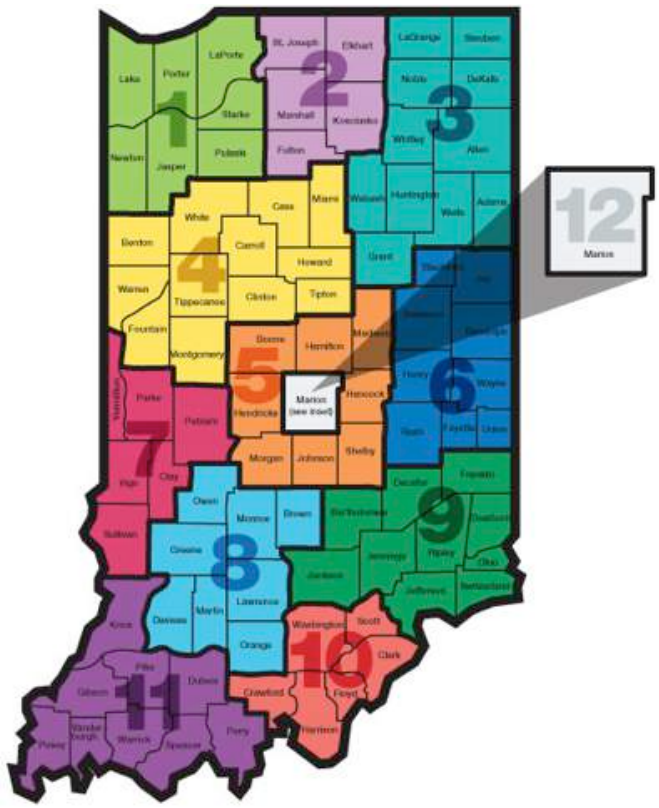

Figure 5.4 Counties comprising of Indiana growth regions

There is a historical relationship between relative economic activity (freight commodity flows, workplace commuting, etc.) and VMT. However, caution should be taken when comparing between EGRs because bias can arise when comparing regions with major interstates and other touring routes that contribute to the regional VMT.

For state routes, the annual change in VMT from 2009 to 2012 is shown in Figure 5.5. EGR 5 had the highest VMT in 2009 and 2010 and EGR 1 had the highest VMT in 2011 and 2012, with both regions' VMT at 5.7 to 6.2 billion annually. Regions 2, 4, 6, and 11 had similar VMT at 2 to 3 billion annually. Both local routes and the statewide total per EGR are shown in Figure 5.6. The trends were similar to the state routes, with EGR 5 and EGR 1 having the highest VMT in Indiana. Regions 3 and 12 were the next highest at 9 to 9.2 billion annually.

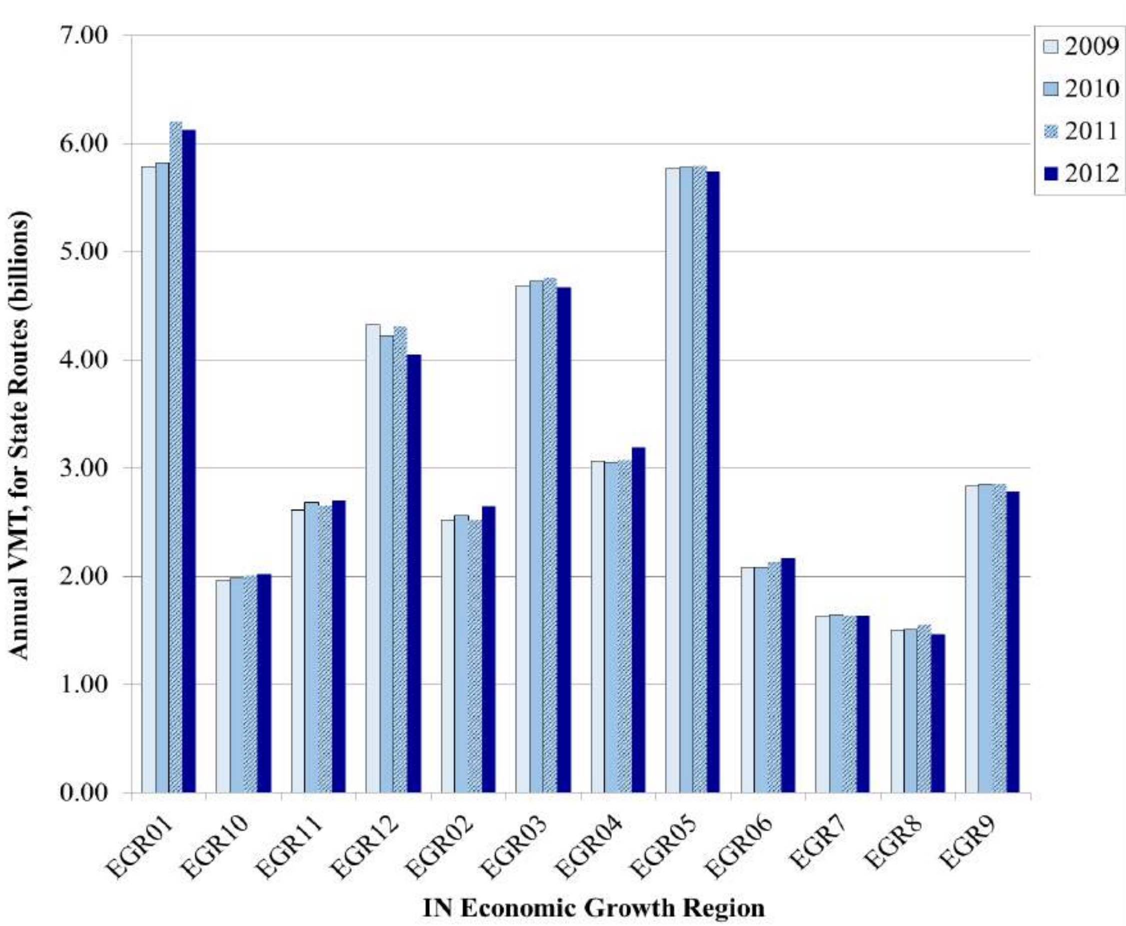

Figure 5.5 Estimated state route VMT by Indiana economic growth region

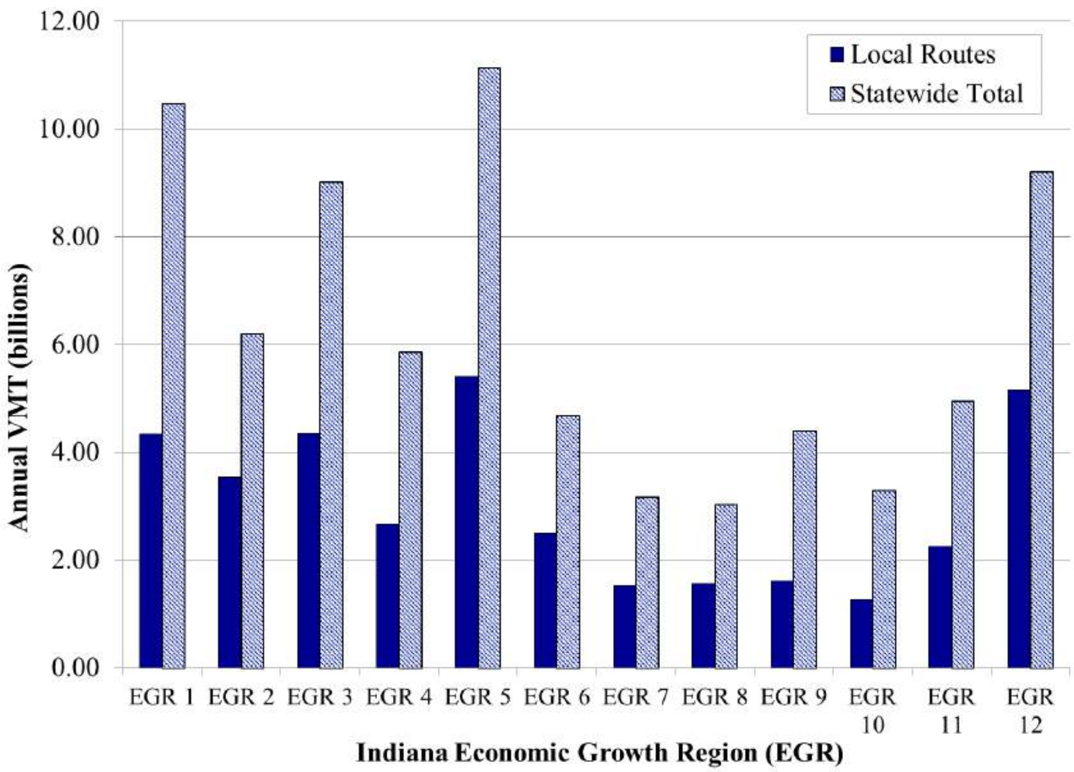

Figure 5.6 Share of local route VMT by Indiana economic growth region

Table 5.6 Annual local and state VMT by Indiana economic growth region

Economic Growth Region	Local Routes VMT	Statewide Total VMT
EGR 1	4.348	10.477
EGR 2	3.546	6.197
EGR 3	4.351	9.022
EGR 4	2.664	5.858
EGR 5	5.398	11.139
EGR 6	2.509	4.679
EGR 7	1.532	3.169
EGR 8	1.572	3.031
EGR 9	1.611	4.396
EGR 10	1.274	3.292
EGR 11	2.253	4.953
EGR 12	5.157	9.202

Local route VMT was highest for EGR 5, with EGR 3 and EGR 1 having the next highest. The lowest local route VMT was EGR 7 and EGR 8 in southwestern Indiana. As may be expected, the urban areas of Lake, Marion, and Allen County contributed to a high VMT for regions containing these counties, along with regions containing major freeway corridors.

5.1.4 Aggregation by Link-Level Sample (HPMS)

To compare the results from estimation using the link-level sampling incorporated into the HPMS, data were compiled from HPMS submittals for 2009 to 2013 shown by FHWA functional classes. These statewide VMT estimates are expected to be close to this study's estimates because they also are based on an extensive sample of traffic counts for each functional class. However, the local and collector classes have a lower reliability due to the limitations of relying solely on one approach as discussed earlier. As shown for 2009 to 2013 in Table 5.7., the statewide VMT is shown by functional classes for interstates, principal arterials, other freeways and expressways, minor arterials, major collectors, minor collectors, and locals. Interstates, FC 1, and Locals, FC 7, had the highest VMT based on the HPMS. The statewide annual VMT is 76.628, 75.761, 76.485, 78.923, and 78.851 billion for 2009, 2010, 2011, 2012, and 2013, respectively.

Table 5.7 Statewide VMT by FHWA functional classes from HPMS submittals

Statewide VMT by Functional Classes	**2009**	**2010**	**2011**	**2012**	**2013**
Interstates (FC 1)	16.726	16.506	17.130	17.238	17.440
Principal Arterials - Other Freeways/Expys (FC2)	1.304	1.339	1.288	1.347	1.339
Principal Arterials - Other (FC3)	15.280	15.055	15.216	15.877	15.845
Minor Arterial (FC4)	11.007	11.818	11.858	12.191	12.617
Major Collector (FC5)	12.818	11.286	11.291	11.214	10.450
Minor Collector (FC6)	1.916	1.916	1.883	2.385	2.368
Locals (FC 7)	17.577	17.840	17.819	18.670	18.791
	76.628	75.761	76.485	78.923	78.851

5.2 Predicted Statewide VMT (Link-Level)

This section contains the predicted Indiana annual VMT at the link-level. Aggregations are provided by statewide totals, route, vehicle class, and functional class.

5.2.1 Aggregation by Year (Statewide)

The predicted aggregated statewide VMT is shown in Table 5.8 for 2009 to 2035, with 2009 to 2012 the benchmark estimation years. All units are shown in billions. The low, medium, and high growth ranges are shown for state and local routes as well as the statewide total.

Table 5.8 Summary of predicted aggregate statewide VMT

	State Routes Annual VMT (billions)			Local Routes Annual VMT (billions)			State Total Annual VMT (billions)		
Year	Low	Medium	High	Low	Medium	High	Low	Medium	High
2009	39.921	39.921	39.921	35.417	35.154	34.893	75.338	75.075	74.813
2010	39.779	39.779	39.779	35.614	35.416	35.218	75.394	75.195	74.998
2011	40.592	40.592	40.592	35.813	35.680	35.547	76.405	76.272	76.139
2012	40.346	40.346	40.346	36.013	35.946	35.879	76.359	76.292	76.225
2013	40.588	40.702	40.817	36.214	36.214	36.214	76.802	76.917	77.031
2014	40.942	41.174	41.407	36.415	36.482	36.549	77.357	77.656	77.956
2015	41.300	41.652	42.007	36.617	36.752	36.887	77.917	78.404	78.894
2016	41.662	42.137	42.616	36.820	37.024	37.228	78.482	79.161	79.844
2017	42.027	42.627	43.234	37.025	37.298	37.573	79.052	79.925	80.807
2018	42.396	43.124	43.863	37.230	37.574	37.920	79.626	80.698	81.783
2019	42.769	43.627	44.501	37.437	37.852	38.271	80.205	81.479	82.772
2020	43.145	44.136	45.149	37.645	38.132	38.625	80.790	82.269	83.775
2021	43.525	44.653	45.808	37.854	38.414	38.982	81.379	83.067	84.791
2022	43.909	45.176	46.478	38.064	38.699	39.343	81.973	83.874	85.821
2023	44.297	45.705	47.158	38.275	38.985	39.707	82.572	84.690	86.865
2024	44.689	46.242	47.849	38.487	39.273	40.074	83.176	85.516	87.923
2025	45.085	46.786	48.551	38.701	39.564	40.445	83.786	86.350	88.996
2026	45.485	47.337	49.264	38.916	39.857	40.819	84.401	87.194	90.083
2027	45.889	47.895	49.989	39.132	40.152	41.197	85.021	88.047	91.186
2028	46.297	48.460	50.725	39.349	40.449	41.578	85.646	88.909	92.303
2029	46.710	49.033	51.474	39.567	40.748	41.962	86.277	89.781	93.436
2030	47.126	49.613	52.234	39.787	41.050	42.350	86.913	90.663	94.585
2031	47.548	50.201	53.007	40.008	41.354	42.742	87.555	91.555	95.749
2032	47.973	50.797	53.792	40.230	41.660	43.137	88.203	92.457	96.930
2033	48.403	51.401	54.590	40.453	41.968	43.536	88.856	93.369	98.127
2034	48.838	52.013	55.401	40.678	42.278	43.939	89.515	94.291	99.340
2035	49.277	52.633	56.225	40.903	42.591	44.346	90.180	95.224	100.571

In 2035, the statewide VMT was estimated to be from 90.180 to 100.571 billion, with an average of 95.224 billion. Of these totals in 2035, state routes contributed 49.277 to 56.225 billion and local routes contributed 40.903 to 44.346 billion. These total VMTs for future years are shown in Figure 5.7, with the bottom curve representing the lowest growth rate scenario, the middle curve representing a moderate growth rate scenario, and the top curve representing the highest growth rate scenario. The range of VMT remains close until 2022 and then the gap widens far into the future, indicating the stochastic nature of long-term traffic forecasting.

It is noted that economic changes, population shifts, and other exogenous factors may greatly influence these predictions. Therefore, these predictions should be used to gauge the trends in statewide VMT but must be updated when more recent traffic data are available.

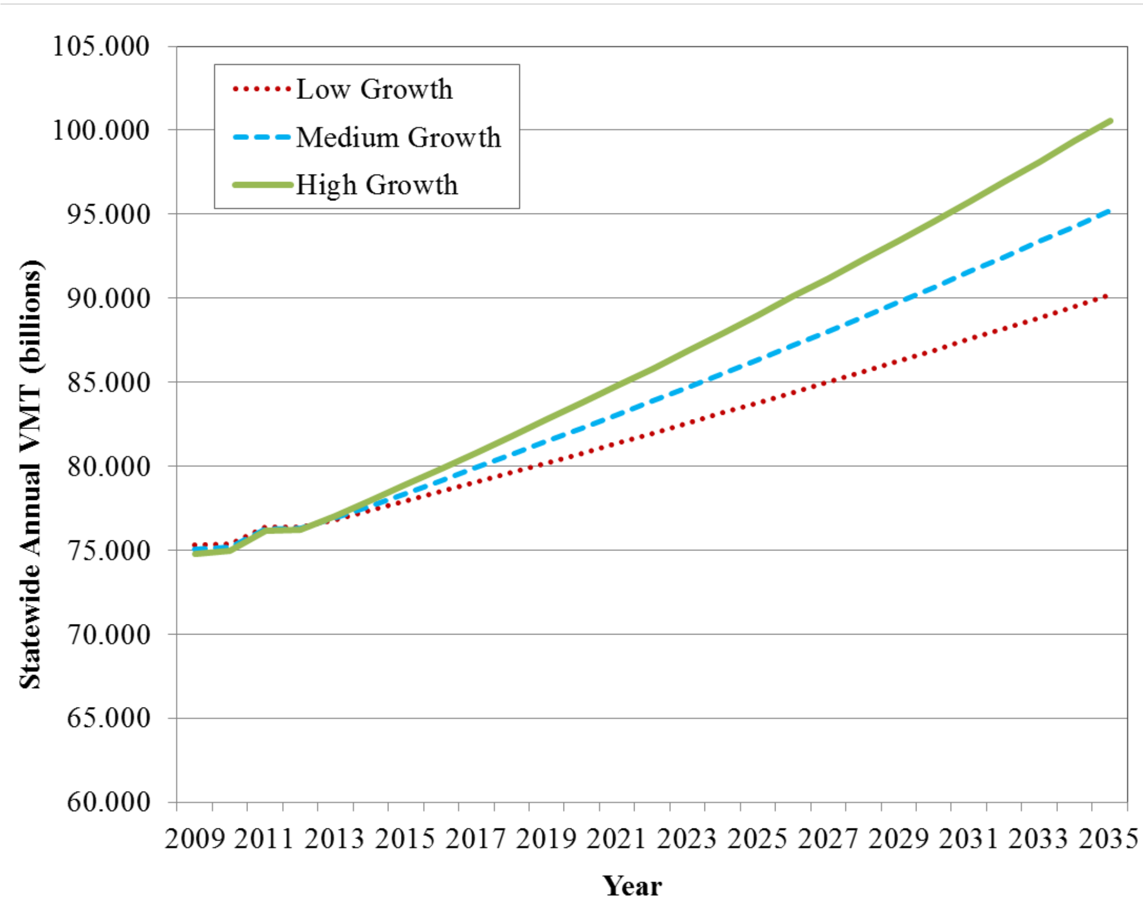

Figure 5.7 Predicted statewide VMT for varying traffic growth rate scenarios

5.2.2 Aggregation by Year (Route)

A comparison of current and future interstate VMT is shown in Table 5.9. This aggregation is for all interstate routes in Indiana, including the Indiana Toll Road with 2011 link-level data. The four-year weighted average traffic distributions by vehicle classes were applied for aggregating by routes. The route aggregations are for mainline roads and do not contain ramps. Based on the projections shown for 2035, I-65 had the highest total VMT, and then I-70, followed closely by I-69. With the major I-69 construction underway, this may lead to I-69 having the second highest interstate VMT. Additionally, I-465 has the fourth highest interstate VMT.

Table 5.9 Comparison of current and projected interstate VMT by Route

	Annual VMT (millions)												
Year	**I265**	**I275**	**I465**	**I469**	**I64**	**I65**	**I69**	**I70**	**I74**	**I80**	**I865**	**I90**	**I94**
2009	119.72	41.75	2195.50	231.33	776.04	4659.68	2303.28	2496.74	1253.95	680.61	47.37	1447.92	497.92
2010	120.19	39.62	2199.13	242.03	839.71	4568.20	2295.73	2479.85	1203.10	760.79	47.55	1447.92	499.91
2011	121.35	39.72	2113.81	245.68	863.05	4706.30	2324.79	2649.97	1180.99	897.54	50.55	1447.92	607.13
2012	119.66	39.79	2045.35	243.13	885.96	4764.30	2319.65	2398.38	1167.64	760.76	50.65	1447.92	609.35
2013	122.49	40.19	2066.30	245.62	895.03	4813.08	2343.41	2422.94	1179.60	768.55	51.17	1462.75	615.59
2014	123.74	40.61	2087.46	248.13	904.20	4862.37	2367.40	2447.75	1191.68	776.42	51.69	1477.73	621.89
2015	125.01	41.02	2108.83	250.67	913.46	4912.16	2391.65	2472.82	1203.88	784.37	52.22	1492.86	628.26
2016	126.29	41.44	2130.43	253.24	922.81	4962.46	2416.14	2498.14	1216.21	792.40	52.76	1508.15	634.69
2017	127.58	41.87	2152.24	255.83	932.26	5013.28	2440.88	2523.72	1228.66	800.51	53.30	1523.59	641.19
2018	128.89	42.29	2174.28	258.45	941.81	5064.61	2465.87	2549.56	1241.24	808.71	53.84	1539.19	647.76
2019	130.21	42.73	2196.55	261.10	951.45	5116.47	2491.12	2575.67	1253.95	816.99	54.39	1554.95	654.39
2020	131.54	43.17	2219.04	263.77	961.20	5168.87	2516.63	2602.05	1266.80	825.36	54.95	1570.88	661.09
2021	132.89	43.61	2241.76	266.47	971.04	5221.80	2542.40	2628.69	1279.77	833.81	55.51	1586.96	667.86
2022	134.25	44.05	2264.72	269.20	980.98	5275.27	2568.44	2655.61	1292.87	842.35	56.08	1603.21	674.70
2023	135.63	44.50	2287.91	271.96	991.03	5329.29	2594.74	2682.80	1306.11	850.97	56.66	1619.63	681.61
2024	137.02	44.96	2311.34	274.74	1001.18	5383.86	2621.31	2710.28	1319.49	859.69	57.24	1636.21	688.59
2025	138.42	45.42	2335.00	277.56	1011.43	5438.99	2648.15	2738.03	1333.00	868.49	57.82	1652.97	695.64
2026	139.84	45.89	2358.91	280.40	1021.78	5494.68	2675.27	2766.07	1346.65	877.38	58.41	1669.89	702.76
2027	141.27	46.36	2383.07	283.27	1032.25	5550.95	2702.66	2794.39	1360.44	886.37	59.01	1686.99	709.96
2028	142.71	46.83	2407.47	286.17	1042.82	5607.79	2730.34	2823.00	1374.37	895.44	59.62	1704.27	717.23
2029	144.18	47.31	2432.13	289.10	1053.50	5665.21	2758.30	2851.91	1388.44	904.61	60.23	1721.72	724.57
2030	145.65	47.79	2457.03	292.06	1064.28	5723.23	2786.54	2881.12	1402.66	913.88	60.84	1739.35	731.99
2031	147.14	48.28	2482.19	295.05	1075.18	5781.83	2815.08	2910.62	1417.02	923.23	61.47	1757.16	739.49
2032	148.65	48.78	2507.61	298.07	1086.19	5841.04	2843.90	2940.42	1431.53	932.69	62.10	1775.16	747.06
2033	150.17	49.28	2533.29	301.13	1097.31	5900.85	2873.02	2970.53	1446.19	942.24	62.73	1793.33	754.71
2034	151.71	49.78	2559.23	304.21	1108.55	5961.27	2902.44	3000.95	1461.00	951.89	63.37	1811.70	762.44
2035	153.26	50.29	2585.43	307.32	1119.90	6022.32	2932.16	3031.68	1475.96	961.64	64.02	1830.25	770.25

The distribution for vehicle classes along interstate route are shown in Table 5.10. Motorcycles were consistently at 0.4-0.5% for all routes. Automobiles varied from 50.4% for I-70 to 65.6% for I-265. Light-duty trucks varied from 17.1% for I-70 to 22.2% for I-265. Buses were consistent across all the routes at 0.2 to 0.4%. Class 5 trucks varied from 2.4 to 4.6% on the I-94 route. Single-unit trucks were consistent across most interstate routes. The distribution of class 9 trucks varied greatly, with I-70 containing the highest (23.8%) and I-275 and I-265 containing the lowest (9.7% and 7.3%). Finally, combination trucks were consistently below 1.0% for all interstate routes, with I-64 and I-74 containing the highest percentages.

The combined distribution of single-unit truck classes 5-7 is shown in Figure 5.8 for interstate routes in Indiana. It was observed that I-65 contained the majority of the total single truck VMT (29.8%), and I-70 had the next highest share of single-unit truck VMT (19.2%). Interstates 74, 80, 865, 94, 265, 275, 469, and 64 all had less than 10.0% of the VMT share for single-unit trucks.

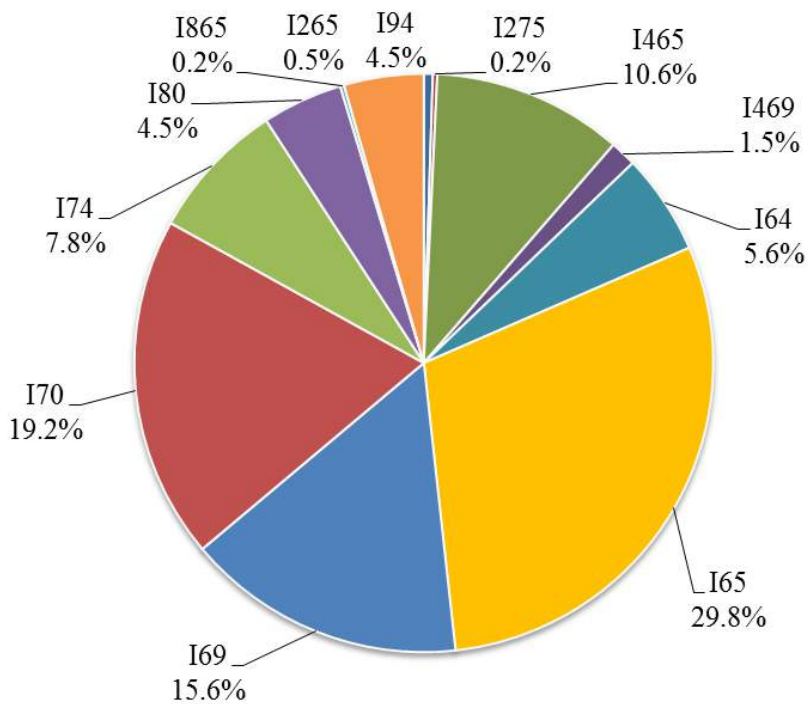

Figure 5.8 Distribution of single-unit truck VMT by interstate route

Table 5.10 Interstate vehicle class distribution by route

4-Year Weighted Average Traffic Distribution by Route													
Route	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**	**Class 9**	**Class 10**	**Class 11**	**Class 12**	**Class 13**
I 265	0.45%	65.58%	22.23%	0.21%	2.38%	0.40%	0.06%	0.74%	7.29%	0.12%	0.37%	0.14%	0.04%
I 275	0.42%	61.28%	20.77%	0.31%	3.46%	0.58%	0.09%	1.80%	9.69%	0.28%	0.89%	0.34%	0.09%
I 865	0.41%	59.88%	20.30%	0.22%	2.41%	0.40%	0.06%	0.63%	15.13%	0.10%	0.31%	0.12%	0.03%
I 69	0.39%	55.84%	18.93%	0.37%	4.08%	0.68%	0.11%	1.28%	17.20%	0.20%	0.63%	0.24%	0.06%
I 469	0.39%	55.77%	18.91%	0.32%	3.58%	0.59%	0.10%	0.95%	18.54%	0.15%	0.47%	0.18%	0.05%
I 80	0.39%	55.70%	18.88%	0.30%	3.30%	0.55%	0.09%	1.07%	18.78%	0.17%	0.53%	0.20%	0.05%
I 65	0.37%	53.76%	18.24%	0.35%	3.87%	0.64%	0.10%	1.19%	20.42%	0.19%	0.59%	0.22%	0.06%
I 74	0.37%	53.32%	18.14%	0.35%	3.93%	0.65%	0.10%	1.60%	20.10%	0.25%	0.79%	0.30%	0.08%
I 64	0.36%	52.64%	17.85%	0.35%	3.89%	0.65%	0.10%	1.62%	21.10%	0.26%	0.80%	0.30%	0.08%
I 94	0.35%	50.83%	17.25%	0.42%	4.61%	0.77%	0.12%	1.34%	23.12%	0.21%	0.66%	0.25%	0.07%
I 70	0.35%	50.42%	17.11%	0.39%	4.38%	0.73%	0.12%	1.43%	23.80%	0.23%	0.71%	0.27%	0.07%

The distribution of single-trailer truck VMT for classes 8-10, is shown by the interstate route in Figure 5.9. Again, I-65 constituted the majority (31.4%), with I-70 as the second highest (20.5%), followed by I-69 (14.2%). A relatively similar distribution was observed between single-unit and single-trailer trucks. Finally, the distribution of combination truck VMT classes 11-13 is shown by the interstate route in Figure 5.10. Similar distributions to single-unit trucks were seen with I-65 (29.4%), I-70 (19.6%), and I-69 (15.6%), with these routes containing 64.6% of the total combination truck VMT.

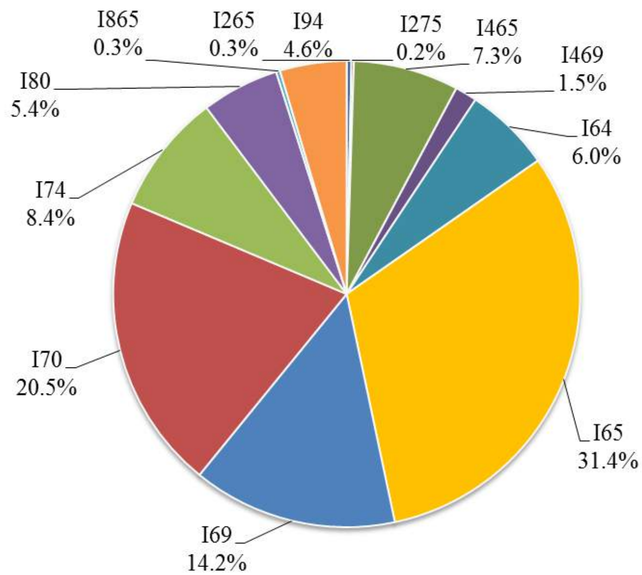

Figure 5.9 Distribution of single-trailer truck VMT by interstate route

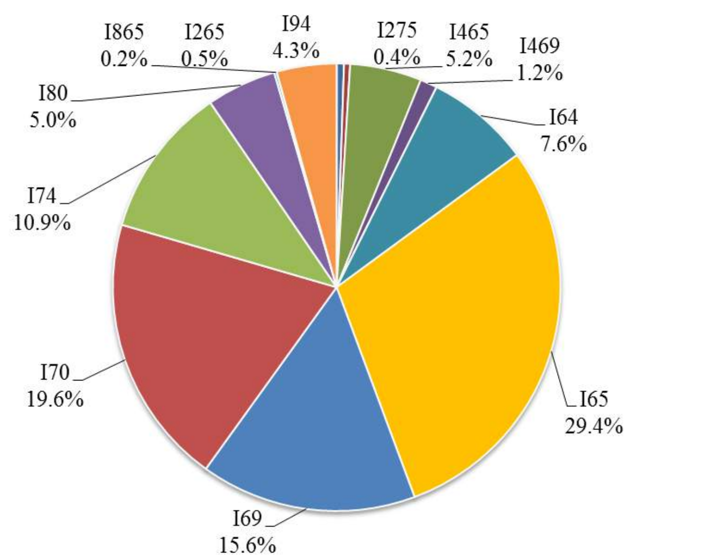

Figure 5.10 Distribution of combination truck VMT by interstate route

The commercial VMT was analyzed for each interstate route between 2009 and 2012, as presented in Figure 5.11. On average, I-65 contains the highest commercial trucking VMT, estimated as approximately 1.4 billion in 2009 and 2010, 0.8 billion in 2011, and 1.0 billion in 2012. The routes in order from the highest to the lowest commercial VMT were as follows: I-70, I-69, I-465, I-74, I-64, I-80, I-469, and I-265. Note that three routes, I-65, I-70, and I-70, had an average annual commercial VMT of greater than 400 million.

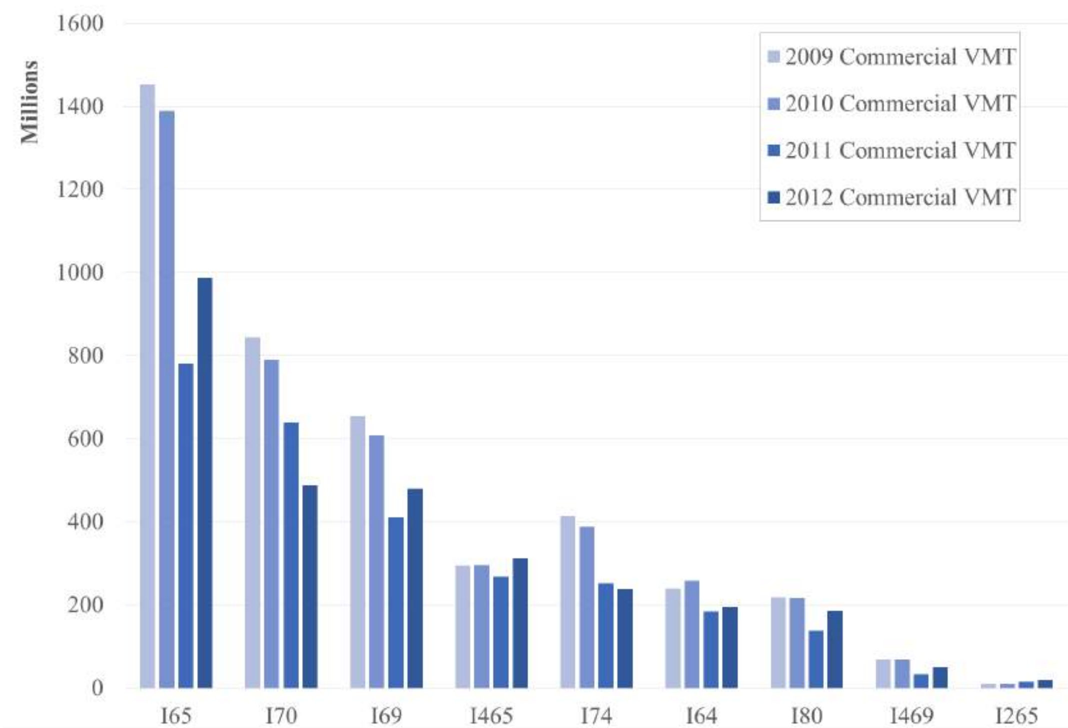

Figure 5.11 Ranking of Interstate Commercial VMT

Aggregations of the annual VMT by US highway route are provided in Table 5.11 with all units in millions for the 20 US routes, which were based on the link-level AADT. The highest VMT was attributed to US-31, at 2,244 million in 2035, with US-41 next highest at 1,649 million. Similarly, aggregated results for select state roads are given in Table 5.12. There are over 200 state roads in Indiana, and about 20 of the routes with a predicted 2035 VMT of above 300 million were chosen to represent the highest state road VMT in Indiana. SR-37 is predicted to have the highest 2035 VMT of around 1,253 million. Other state roads with significant future VMT include SR-3 and SR-62.

Table 5.11 Comparison of current and projected US Road VMT

	US Road Annual VMT (millions)																			
Year	**US12**	**US131**	**US136**	**US150**	**US20**	**US224**	**US231**	**US24**	**US27**	**US30**	**US31**	**US33**	**US35**	**US36**	**US40**	**US41**	**US421**	**US50**	**US52**	**US6**
2009	164.08	2.06	113.43	154.09	711.51	63.83	672.61	472.47	362.59	1048.21	1704.13	219.43	395.35	389.26	508.73	1196.27	376.17	560.68	356.61	347.06
2010	164.42	1.60	114.22	154.13	699.04	63.98	668.79	474.70	354.85	1075.13	1709.92	231.68	397.78	395.26	519.59	1195.76	378.15	571.38	356.39	333.09
2011	193.50	1.88	114.53	163.78	684.17	95.63	671.07	398.06	331.15	1066.15	1746.20	135.89	395.36	404.83	501.58	1194.85	448.07	590.31	328.78	347.95
2012	200.14	2.15	115.22	160.78	710.03	67.61	694.98	406.24	337.43	1014.03	1671.74	242.21	398.38	407.14	537.87	1235.44	423.73	601.22	357.63	363.06
2013	202.79	2.18	116.78	163.11	716.50	68.58	704.14	410.46	341.70	1025.05	1693.25	245.31	403.52	412.70	544.90	1250.99	429.41	608.56	362.48	367.58
2014	205.46	2.21	118.36	165.48	723.05	69.57	713.42	414.74	346.02	1036.22	1715.04	248.45	408.74	418.33	552.03	1266.75	435.16	616.00	367.39	372.15
2015	208.17	2.24	119.96	167.88	729.70	70.57	722.82	419.08	350.40	1047.53	1737.11	251.63	414.03	424.03	559.25	1282.71	441.00	623.53	372.37	376.78
2016	210.92	2.27	121.59	170.32	736.44	71.58	732.35	423.47	354.84	1058.99	1759.47	254.85	419.40	429.82	566.57	1298.87	446.91	631.15	377.43	381.47
2017	213.70	2.29	123.23	172.79	743.27	72.61	742.01	427.92	359.33	1070.59	1782.13	258.11	424.85	435.68	573.98	1315.25	452.90	638.88	382.55	386.22
2018	216.52	2.32	124.90	175.30	750.20	73.66	751.80	432.42	363.88	1082.34	1805.07	261.41	430.38	441.63	581.49	1331.84	458.97	646.71	387.73	391.03
2019	219.38	2.35	126.59	177.84	757.23	74.71	761.72	436.99	368.49	1094.24	1828.32	264.76	435.98	447.65	589.09	1348.64	465.13	654.63	393.00	395.90
2020	222.28	2.38	128.30	180.43	764.36	75.79	771.77	441.60	373.16	1106.29	1851.87	268.15	441.67	453.76	596.80	1365.67	471.37	662.66	398.33	400.84
2021	225.21	2.41	130.04	183.05	771.58	76.88	781.96	446.28	377.88	1118.49	1875.73	271.58	447.43	459.96	604.61	1382.91	477.69	670.80	403.73	405.84
2022	228.19	2.45	131.80	185.71	778.92	77.98	792.29	451.02	382.67	1130.85	1899.90	275.06	453.28	466.23	612.52	1400.38	484.10	679.04	409.21	410.90
2023	231.20	2.48	133.58	188.40	786.35	79.11	802.76	455.82	387.52	1143.37	1924.39	278.58	459.22	472.60	620.53	1418.08	490.59	687.38	414.77	416.03
2024	234.25	2.51	135.39	191.14	793.89	80.24	813.37	460.68	392.43	1156.05	1949.19	282.14	465.24	479.05	628.65	1436.01	497.18	695.84	420.39	421.23
2025	237.35	2.54	137.22	193.92	801.53	81.40	824.13	465.60	397.41	1168.88	1974.32	285.75	471.35	485.59	636.88	1454.17	503.85	704.40	426.10	426.49
2026	240.48	2.57	139.08	196.74	809.29	82.57	835.03	470.58	402.44	1181.89	1999.77	289.41	477.54	492.22	645.21	1472.56	510.61	713.07	431.89	431.82
2027	243.66	2.61	140.97	199.60	817.15	83.76	846.08	475.63	407.54	1195.06	2025.56	293.12	483.82	498.95	653.65	1491.20	517.46	721.86	437.75	437.22
2028	246.87	2.64	142.87	202.50	825.12	84.96	857.28	480.74	412.71	1208.39	2051.68	296.87	490.20	505.76	662.20	1510.08	524.41	730.76	443.69	442.68
2029	250.14	2.67	144.81	205.44	833.21	86.19	868.63	485.92	417.95	1221.90	2078.15	300.67	496.66	512.67	670.87	1529.20	531.44	739.78	449.72	448.22
2030	253.44	2.71	146.77	208.43	841.41	87.43	880.14	491.16	423.25	1235.58	2104.96	304.52	503.22	519.67	679.64	1548.58	538.58	748.91	455.82	453.83
2031	256.79	2.74	148.76	211.46	849.73	88.69	891.80	496.47	428.61	1249.43	2132.12	308.41	509.88	526.77	688.54	1568.20	545.81	758.16	462.01	459.51
2032	260.18	2.78	150.77	214.53	858.17	89.96	903.63	501.85	434.05	1263.46	2159.63	312.36	516.63	533.97	697.55	1588.08	553.14	767.53	468.29	465.27
2033	263.62	2.81	152.81	217.65	866.72	91.26	915.61	507.30	439.56	1277.67	2187.51	316.36	523.47	541.26	706.67	1608.22	560.57	777.02	474.65	471.10
2034	267.10	2.85	154.88	220.82	875.40	92.57	927.76	512.81	445.13	1292.06	2215.74	320.41	530.42	548.66	715.92	1628.63	568.09	786.64	481.10	477.00
2035	270.63	2.89	156.98	224.03	884.19	93.91	940.08	518.40	450.78	1306.63	2244.35	324.51	537.46	556.16	725.29	1649.29	575.72	796.38	487.63	482.98

Table 5.12 Comparison of selected high volume State Road VMT

	State Road (SR) Annual VMT (millions)																
Year	**SR1**	**SR13**	**SR135**	**SR15**	**SR19**	**SR2**	**SR25**	**SR3**	**SR32**	**SR37**	**SR39**	**SR46**	**SR56**	**SR62**	**SR66**	**SR67**	**SR9**
2009	289.64	215.74	271.17	270.86	235.52	266.12	255.49	507.87	343.72	940.79	188.14	366.55	265.96	542.92	344.98	329.12	486.75
2010	294.95	217.89	275.97	278.06	242.55	270.37	260.36	518.90	345.00	941.77	188.41	368.39	265.81	554.94	345.54	333.26	484.92
2011	301.60	218.52	272.58	276.26	244.25	277.60	245.00	511.18	339.17	965.18	195.64	409.16	256.46	537.89	344.60	346.91	494.07
2012	304.46	233.93	284.97	271.82	252.15	274.13	267.27	523.32	343.01	1009.55	214.86	366.39	247.19	481.07	360.71	373.98	472.27
2013	308.74	237.28	289.04	275.72	255.97	278.09	270.87	530.08	347.71	1018.72	218.05	371.23	250.60	487.28	365.43	378.89	478.68
2014	313.09	240.68	293.16	279.68	259.85	282.10	274.52	536.93	352.47	1028.02	221.28	376.13	254.05	493.58	370.21	383.88	485.19
2015	317.49	244.14	297.35	283.70	263.79	286.17	278.22	543.88	357.31	1037.44	224.57	381.09	257.56	499.97	375.05	388.93	491.78
2016	321.96	247.64	301.59	287.78	267.80	290.30	281.96	550.92	362.20	1046.98	227.91	386.13	261.11	506.45	379.96	394.06	498.47
2017	326.48	251.20	305.90	291.92	271.88	294.49	285.76	558.06	367.17	1056.65	231.31	391.23	264.71	513.01	384.93	399.26	505.25
2018	331.08	254.81	310.27	296.12	276.02	298.74	289.61	565.30	372.20	1066.43	234.76	396.40	268.36	519.67	389.97	404.53	512.13
2019	335.74	258.47	314.70	300.38	280.24	303.06	293.51	572.63	377.31	1076.35	238.27	401.63	272.07	526.43	395.08	409.88	519.10
2020	340.46	262.19	319.19	304.71	284.53	307.43	297.47	580.07	382.48	1086.39	241.84	406.94	275.82	533.27	400.25	415.30	526.17
2021	345.25	265.97	323.75	309.10	288.89	311.87	301.47	587.60	387.73	1096.57	245.46	412.31	279.63	540.22	405.49	420.80	533.34
2022	350.11	269.80	328.37	313.55	293.33	316.37	305.54	595.24	393.05	1106.87	249.15	417.76	283.49	547.26	410.80	426.38	540.61
2023	355.04	273.69	333.06	318.07	297.84	320.94	309.65	602.98	398.44	1117.31	252.90	423.28	287.40	554.39	416.17	432.04	547.99
2024	360.04	277.64	337.82	322.66	302.43	325.58	313.83	610.83	403.90	1127.88	256.70	428.87	291.37	561.63	421.62	437.77	555.46
2025	365.11	281.65	342.65	327.32	307.10	330.28	318.06	618.78	409.45	1138.60	260.58	434.54	295.39	568.98	427.14	443.59	563.04
2026	370.25	285.72	347.55	332.05	311.85	335.05	322.34	626.85	415.06	1149.45	264.52	440.28	299.47	576.42	432.73	449.49	570.73
2027	375.46	289.85	352.51	336.85	316.69	339.89	326.69	635.02	420.76	1160.44	268.52	446.10	303.61	583.97	438.40	455.47	578.53
2028	380.75	294.05	357.55	341.72	321.60	344.81	331.09	643.30	426.54	1171.57	272.59	451.99	307.80	591.62	444.14	461.53	586.43
2029	386.11	298.31	362.66	346.66	326.61	349.79	335.56	651.70	432.39	1182.84	276.73	457.97	312.05	599.39	449.95	467.69	594.45
2030	391.55	302.63	367.85	351.68	331.70	354.84	340.08	660.21	438.33	1194.27	280.94	464.02	316.36	607.26	455.85	473.92	602.57
2031	397.07	307.02	373.11	356.77	336.88	359.97	344.66	668.84	444.34	1205.84	285.23	470.15	320.73	615.24	461.82	480.25	610.82
2032	402.66	311.48	378.44	361.94	342.15	365.18	349.31	677.58	450.45	1217.56	289.58	476.37	325.16	623.34	467.86	486.67	619.17
2033	408.34	316.01	383.85	367.18	347.51	370.46	354.02	686.45	456.63	1229.43	294.01	482.66	329.65	631.55	473.99	493.17	627.65
2034	414.09	320.60	389.34	372.51	352.97	375.81	358.80	695.44	462.90	1241.46	298.52	489.05	334.21	639.88	480.20	499.77	636.24
2035	419.93	325.27	394.91	377.91	358.53	381.25	363.64	704.54	469.26	1253.64	303.10	495.51	338.83	648.32	486.49	506.47	644.96

5.2.3 Aggregation by Year (Vehicle Class)

Aggregation by vehicle classes is important for many agency applications, specifically cost allocation and revenue forecasting. The aggregations shown in this section may help users at INDOT, MPOs, and other organizations, obtain more reliable inputs for a wide-range of applications. However, predictions of over 20 years based on observed data are meant to provide the user with the trends and a coarse estimate of VMT. Economic and demographic shifts and other exogenous factors may greatly affect the resulting annual VMT estimate.

These aggregations include both mainline and ramp segments. The predicted statewide VMT for vehicle classes 1 to 3 is shown in Table 5.13, vehicle classes 4 to 6 is shown in Table 5.14, vehicle classes 7 to 9 in Table 5.15, vehicle classes 10 to 11 in Table 5.16, and vehicle classes 12 to 13 in Table 5.17. The low, medium, and high ranges are given for each vehicle class shown, representing the annual VMT for 2009 to 2035, with all units in millions within Table 5.13 to Table 5.17.

Table 5.13 Predicted statewide VMT for Class 1 to Class 3 vehicles

	Class 1 AVMT (billions)			Class 2 AVMT (billions)			Class 3 AVMT (billions)		
Year	Low	Med	High	Low	Med	High	Low	Med	High
2009	0.409	0.407	0.406	46.656	46.483	46.311	18.648	18.575	18.502
2010	0.409	0.408	0.407	46.654	46.523	46.393	18.666	18.611	18.556
2011	0.423	0.422	0.422	48.683	48.596	48.510	19.591	19.554	19.517
2012	0.417	0.417	0.416	47.861	47.818	47.774	19.084	19.065	19.047
2013	0.420	0.420	0.421	48.042	48.111	48.180	19.231	19.257	19.283
2014	0.423	0.424	0.426	48.386	48.570	48.754	19.367	19.438	19.509
2015	0.426	0.428	0.431	48.734	49.033	49.335	19.504	19.621	19.739
2016	0.429	0.432	0.436	49.084	49.502	49.924	19.642	19.806	19.972
2017	0.432	0.436	0.441	49.437	49.976	50.520	19.782	19.993	20.207
2018	0.435	0.441	0.446	49.793	50.455	51.125	19.922	20.182	20.446
2019	0.438	0.445	0.452	50.152	50.939	51.738	20.064	20.374	20.688
2020	0.441	0.449	0.457	50.514	51.428	52.359	20.207	20.567	20.933
2021	0.444	0.453	0.462	50.879	51.923	52.988	20.351	20.762	21.181
2022	0.447	0.458	0.468	51.247	52.423	53.626	20.496	20.959	21.433
2023	0.451	0.462	0.473	51.618	52.928	54.272	20.643	21.159	21.688
2024	0.454	0.466	0.479	51.992	53.439	54.928	20.790	21.360	21.947
2025	0.457	0.471	0.485	52.369	53.956	55.592	20.939	21.564	22.209
2026	0.460	0.475	0.491	52.750	54.478	56.265	21.090	21.770	22.474
2027	0.464	0.480	0.497	53.134	55.006	56.947	21.241	21.979	22.743
2028	0.467	0.484	0.503	53.521	55.540	57.639	21.394	22.189	23.016
2029	0.470	0.489	0.509	53.912	56.080	58.340	21.548	22.402	23.292
2030	0.474	0.494	0.515	54.306	56.625	59.050	21.703	22.617	23.572
2031	0.477	0.499	0.521	54.703	57.177	59.771	21.860	22.835	23.856
2032	0.481	0.503	0.527	55.104	57.735	60.501	22.018	23.055	24.143
2033	0.484	0.508	0.534	55.508	58.300	61.241	22.177	23.277	24.435
2034	0.488	0.513	0.540	55.916	58.870	61.991	22.338	23.502	24.730
2035	0.491	0.518	0.547	56.328	59.447	62.752	22.500	23.729	25.030

Table 5.14 Predicted statewide VMT for Class 4 to Class 6 vehicles

	Class 4 AVMT (billions)			Class 5 AVMT (billions)			Class 6 AVMT (billions)		
Year	Low	Med	High	Low	Med	High	Low	Med	High
2009	0.142	0.141	0.141	1.788	1.785	1.781	0.569	0.567	0.566
2010	0.142	0.142	0.141	1.793	1.791	1.788	0.574	0.573	0.571
2011	0.129	0.129	0.128	1.777	1.774	1.772	0.787	0.786	0.784
2012	0.168	0.168	0.168	2.305	2.303	2.302	0.977	0.976	0.975
2013	0.147	0.147	0.147	1.938	1.941	1.945	0.735	0.736	0.737
2014	0.148	0.149	0.149	1.953	1.961	1.970	0.740	0.743	0.746
2015	0.149	0.150	0.151	1.968	1.981	1.995	0.745	0.750	0.755
2016	0.150	0.152	0.153	1.983	2.002	2.021	0.751	0.757	0.763
2017	0.151	0.153	0.155	1.998	2.022	2.047	0.756	0.764	0.773
2018	0.153	0.155	0.157	2.014	2.043	2.073	0.762	0.772	0.782
2019	0.154	0.157	0.159	2.029	2.064	2.100	0.767	0.779	0.791
2020	0.155	0.158	0.161	2.045	2.086	2.127	0.773	0.786	0.800
2021	0.156	0.160	0.164	2.061	2.107	2.155	0.778	0.794	0.810
2022	0.158	0.162	0.166	2.077	2.129	2.183	0.784	0.801	0.820
2023	0.159	0.163	0.168	2.093	2.151	2.211	0.789	0.809	0.830
2024	0.160	0.165	0.170	2.110	2.174	2.240	0.795	0.817	0.839
2025	0.161	0.167	0.172	2.126	2.196	2.269	0.801	0.825	0.850
2026	0.163	0.169	0.175	2.143	2.219	2.298	0.806	0.833	0.860
2027	0.164	0.170	0.177	2.160	2.242	2.328	0.812	0.841	0.870
2028	0.165	0.172	0.179	2.177	2.266	2.359	0.818	0.849	0.881
2029	0.167	0.174	0.182	2.194	2.290	2.390	0.824	0.857	0.891
2030	0.168	0.176	0.184	2.211	2.314	2.421	0.830	0.865	0.902
2031	0.169	0.178	0.187	2.229	2.338	2.453	0.836	0.874	0.913
2032	0.171	0.180	0.189	2.246	2.363	2.485	0.842	0.882	0.924
2033	0.172	0.182	0.192	2.264	2.387	2.518	0.848	0.891	0.935
2034	0.173	0.184	0.194	2.282	2.413	2.551	0.855	0.899	0.947
2035	0.175	0.186	0.197	2.300	2.438	2.585	0.861	0.908	0.958

Table 5.15 Predicted statewide VMT for Class 7 to Class 9 vehicles

	Class 7 AVMT (billions)			Class 8 AVMT (billions)			Class 9 AVMT (billions)		
Year	Low	Med	High	Low	Med	High	Low	Med	High
2009	0.170	0.169	0.169	0.600	0.599	0.598	6.049	6.040	6.032
2010	0.173	0.172	0.172	0.602	0.601	0.600	6.081	6.074	6.068
2011	0.252	0.251	0.251	0.389	0.388	0.388	4.124	4.120	4.116
2012	0.316	0.315	0.315	0.458	0.458	0.458	4.536	4.535	4.534
2013	0.230	0.230	0.231	0.519	0.520	0.521	5.264	5.276	5.288
2014	0.232	0.233	0.233	0.523	0.525	0.528	5.306	5.333	5.359
2015	0.233	0.235	0.236	0.527	0.531	0.535	5.349	5.390	5.431
2016	0.235	0.237	0.239	0.531	0.537	0.542	5.393	5.448	5.504
2017	0.237	0.239	0.242	0.536	0.542	0.549	5.437	5.507	5.578
2018	0.238	0.241	0.244	0.540	0.548	0.557	5.481	5.567	5.654
2019	0.240	0.244	0.247	0.544	0.554	0.564	5.526	5.627	5.730
2020	0.242	0.246	0.250	0.549	0.560	0.572	5.571	5.688	5.808
2021	0.243	0.248	0.253	0.553	0.566	0.579	5.617	5.750	5.887
2022	0.245	0.250	0.256	0.558	0.572	0.587	5.663	5.813	5.967
2023	0.247	0.253	0.259	0.562	0.578	0.595	5.709	5.876	6.048
2024	0.248	0.255	0.262	0.567	0.584	0.603	5.756	5.940	6.130
2025	0.250	0.258	0.265	0.571	0.591	0.611	5.803	6.005	6.214
2026	0.252	0.260	0.268	0.576	0.597	0.619	5.851	6.071	6.299
2027	0.254	0.262	0.271	0.581	0.604	0.628	5.899	6.138	6.386
2028	0.256	0.265	0.275	0.585	0.610	0.636	5.948	6.205	6.473
2029	0.257	0.267	0.278	0.590	0.617	0.645	5.997	6.273	6.562
2030	0.259	0.270	0.281	0.595	0.624	0.654	6.047	6.342	6.652
2031	0.261	0.272	0.284	0.600	0.630	0.663	6.097	6.412	6.744
2032	0.263	0.275	0.288	0.605	0.637	0.672	6.148	6.483	6.837
2033	0.265	0.278	0.291	0.610	0.644	0.681	6.199	6.555	6.932
2034	0.267	0.280	0.295	0.615	0.651	0.690	6.251	6.627	7.028
2035	0.269	0.283	0.298	0.620	0.658	0.699	6.303	6.701	7.125

Table 5.16 Predicted statewide VMT for Class 10 to Class 11 vehicles

	Class 10 AVMT (billions)			**Class 11 AVMT (billions)**		
Year	Low	Med	High	Low	Med	High
2009	0.090	0.089	0.089	0.141	0.141	0.141
2010	0.090	0.089	0.089	0.136	0.136	0.136
2011	0.058	0.058	0.058	0.085	0.085	0.085
2012	0.068	0.068	0.068	0.108	0.108	0.108
2013	0.077	0.078	0.078	0.119	0.120	0.120
2014	0.078	0.078	0.079	0.120	0.121	0.122
2015	0.079	0.079	0.080	0.121	0.122	0.123
2016	0.079	0.080	0.081	0.122	0.124	0.125
2017	0.080	0.081	0.082	0.123	0.125	0.127
2018	0.081	0.082	0.083	0.124	0.126	0.129
2019	0.081	0.083	0.084	0.125	0.128	0.130
2020	0.082	0.084	0.085	0.127	0.129	0.132
2021	0.082	0.084	0.086	0.128	0.131	0.134
2022	0.083	0.085	0.088	0.129	0.132	0.136
2023	0.084	0.086	0.089	0.130	0.134	0.138
2024	0.085	0.087	0.090	0.131	0.135	0.140
2025	0.085	0.088	0.091	0.132	0.137	0.142
2026	0.086	0.089	0.092	0.133	0.139	0.144
2027	0.087	0.090	0.094	0.134	0.140	0.146
2028	0.087	0.091	0.095	0.136	0.142	0.148
2029	0.088	0.092	0.096	0.137	0.143	0.150
2030	0.089	0.093	0.098	0.138	0.145	0.153
2031	0.089	0.094	0.099	0.139	0.147	0.155
2032	0.090	0.095	0.100	0.140	0.148	0.157
2033	0.091	0.096	0.102	0.142	0.150	0.159
2034	0.092	0.097	0.103	0.143	0.152	0.162
2035	0.092	0.098	0.104	0.144	0.154	0.164

Table 5.17 Predicted statewide VMT for Class 12 to Class 13 vehicles

	Class 12 AVMT (billions)			**Class 13 AVMT (billions)**		
Year	Low	Med	High	Low	Med	High
2009	0.049	0.049	0.049	0.028	0.028	0.028
2010	0.047	0.047	0.047	0.028	0.028	0.028
2011	0.029	0.029	0.029	0.078	0.078	0.078
2012	0.038	0.038	0.038	0.021	0.021	0.021
2013	0.042	0.042	0.042	0.039	0.039	0.039
2014	0.042	0.042	0.042	0.040	0.040	0.040
2015	0.042	0.043	0.043	0.040	0.040	0.041
2016	0.043	0.043	0.044	0.040	0.041	0.041
2017	0.043	0.044	0.044	0.041	0.041	0.042
2018	0.043	0.044	0.045	0.041	0.042	0.042
2019	0.044	0.045	0.045	0.041	0.042	0.043
2020	0.044	0.045	0.046	0.042	0.043	0.043
2021	0.044	0.046	0.047	0.042	0.043	0.044
2022	0.045	0.046	0.047	0.042	0.043	0.045
2023	0.045	0.047	0.048	0.043	0.044	0.045
2024	0.046	0.047	0.049	0.043	0.044	0.046
2025	0.046	0.048	0.050	0.043	0.045	0.047
2026	0.046	0.048	0.050	0.044	0.045	0.047
2027	0.047	0.049	0.051	0.044	0.046	0.048
2028	0.047	0.049	0.052	0.044	0.046	0.049
2029	0.048	0.050	0.052	0.045	0.047	0.049
2030	0.048	0.051	0.053	0.045	0.048	0.050
2031	0.049	0.051	0.054	0.046	0.048	0.051
2032	0.049	0.052	0.055	0.046	0.049	0.051
2033	0.049	0.052	0.056	0.046	0.049	0.052
2034	0.050	0.053	0.056	0.047	0.050	0.053
2035	0.050	0.054	0.057	0.047	0.050	0.054

The results for the grouped annual VMT for single-trailer trucks and combination trucks are presented in Table 5.18. Single-trailer trucks represent truck classes 8 to 10, and multi-trailer trucks represent truck classes 11 to 13. In 2009, single-trailer truck VMT ranged from 6,718 to 6,738 million and combination trucks ranged around 218 million. By 2035, the single-trailer truck VMT was estimated to be 7,015 to 7,929 million and combination truck VMT is estimated to range from 241 to 274 million.

Table 5.18 Predicted statewide VMT for single-trailer and combination trucks

	Classes 8-10: Single-Trailer Truck AVMT (billions)			**Classes 11-13: Combination Truck AVMT (billions)**		
Year	Low	Med	High	Low	Med	High
2009	6.738	6.729	6.719	0.219	0.218	0.218
2010	6.772	6.764	6.757	0.212	0.212	0.212
2011	4.571	4.566	4.562	0.193	0.193	0.193
2012	5.063	5.062	5.060	0.168	0.168	0.168
2013	5.860	5.873	5.886	0.200	0.201	0.201
2014	5.907	5.936	5.965	0.202	0.203	0.204
2015	5.955	6.000	6.045	0.203	0.205	0.207
2016	6.003	6.065	6.127	0.205	0.207	0.210
2017	6.052	6.130	6.209	0.207	0.210	0.213
2018	6.102	6.197	6.293	0.209	0.212	0.216
2019	6.151	6.264	6.378	0.210	0.215	0.219
2020	6.201	6.332	6.465	0.212	0.217	0.222
2021	6.252	6.401	6.552	0.214	0.219	0.225
2022	6.303	6.470	6.641	0.216	0.222	0.228
2023	6.355	6.541	6.732	0.218	0.224	0.231
2024	6.407	6.612	6.823	0.220	0.227	0.235
2025	6.460	6.684	6.916	0.222	0.230	0.238
2026	6.513	6.757	7.011	0.223	0.232	0.241
2027	6.567	6.831	7.107	0.225	0.235	0.245
2028	6.621	6.906	7.204	0.227	0.238	0.248
2029	6.675	6.982	7.303	0.229	0.240	0.252
2030	6.731	7.059	7.404	0.231	0.243	0.256
2031	6.786	7.136	7.505	0.233	0.246	0.259
2032	6.843	7.215	7.609	0.235	0.249	0.263
2033	6.900	7.295	7.714	0.237	0.252	0.267
2034	6.957	7.376	7.821	0.239	0.255	0.271
2035	7.015	7.457	7.929	0.242	0.258	0.275

5.2.4 Aggregation by Year (Road Type)

This section provides additional aggregations for state routes by road type or major road designation. The Interstate VMT total shown in Table 5.19 includes mainline, ramps, and the Indiana Toll Road (I-90). The totals provided for US and state roads also include all mainline and ramp segments. The interstate VMT for 2015 ranged from 18.146 to 18.410 billion, the US Roads VMT was from 10.303 to 10.493 billion, and the State Roads VMT was from 12.850 to 13.103 billion.

Table 5.19 Predicted statewide VMT by Road Type

Year	**Interstates VMT (billions)**			**US Roads VMT (billions)**			**State Roads VMT (billions)**			**Local Roads VMT (billions)**		
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
2009	17.782	17.782	17.782	9.876	9.876	9.876	12.263	12.263	12.263	35.417	35.154	34.893
2010	17.492	17.492	17.492	9.916	9.916	9.916	12.371	12.371	12.371	35.614	35.416	35.218
2011	18.057	18.057	18.057	9.954	9.954	9.954	12.581	12.581	12.581	35.813	35.680	35.547
2012	17.864	17.864	17.864	10.015	10.015	10.015	12.468	12.468	12.468	36.013	35.946	35.879
2013	17.884	17.927	17.970	10.110	10.141	10.171	12.594	12.635	12.676	36.214	36.214	36.214
2014	18.015	18.102	18.189	10.206	10.268	10.331	12.721	12.804	12.888	36.415	36.482	36.549
2015	18.146	18.278	18.410	10.303	10.398	10.493	12.850	12.977	13.103	36.617	36.752	36.887
2016	18.279	18.456	18.635	10.402	10.529	10.658	12.981	13.151	13.323	36.820	37.024	37.228
2017	18.413	18.636	18.862	10.501	10.662	10.825	13.113	13.328	13.547	37.025	37.298	37.573
2018	18.548	18.818	19.092	10.602	10.797	10.996	13.246	13.508	13.774	37.230	37.574	37.920
2019	18.683	19.002	19.326	10.704	10.934	11.170	13.381	13.690	14.006	37.437	37.852	38.271
2020	18.820	19.188	19.562	10.807	11.073	11.346	13.518	13.875	14.242	37.645	38.132	38.625
2021	18.958	19.375	19.801	10.911	11.214	11.526	13.656	14.063	14.482	37.854	38.414	38.982
2022	19.097	19.565	20.043	11.016	11.357	11.708	13.796	14.254	14.726	38.064	38.699	39.343
2023	19.237	19.756	20.288	11.123	11.502	11.894	13.937	14.447	14.975	38.275	38.985	39.707
2024	19.378	19.949	20.537	11.230	11.649	12.083	14.080	14.643	15.229	38.487	39.273	40.074
2025	19.521	20.145	20.788	11.339	11.798	12.276	14.225	14.843	15.487	38.701	39.564	40.445
2026	19.664	20.342	21.043	11.450	11.950	12.471	14.371	15.045	15.750	38.916	39.857	40.819
2027	19.808	20.542	21.301	11.561	12.103	12.670	14.520	15.250	16.017	39.132	40.152	41.197
2028	19.954	20.743	21.563	11.674	12.259	12.873	14.669	15.458	16.290	39.349	40.449	41.578
2029	20.100	20.946	21.827	11.788	12.417	13.079	14.821	15.670	16.567	39.567	40.748	41.962
2030	20.248	21.152	22.096	11.904	12.577	13.289	14.975	15.884	16.850	39.787	41.050	42.350
2031	20.397	21.359	22.367	12.021	12.739	13.502	15.130	16.102	17.138	40.008	41.354	42.742
2032	20.547	21.569	22.642	12.139	12.904	13.719	15.287	16.324	17.431	40.230	41.660	43.137
2033	20.698	21.781	22.921	12.259	13.072	13.940	15.447	16.548	17.730	40.453	41.968	43.536
2034	20.850	21.995	23.203	12.380	13.241	14.165	15.608	16.776	18.034	40.678	42.278	43.939
2035	21.004	22.211	23.488	12.502	13.414	14.393	15.771	17.008	18.343	40.903	42.591	44.346

Local routes are comprised of multiple FHWA functional classes; therefore, individual functional class totals, such as for major and minor collectors, cannot be determined using this aggregation. Instead, this study provides the cluster VMT, or grouped counties VMT (2009 to 2035) to allow for regional assessment of VMT across Indiana. The city and county road VMT given in Table 5.20 (units in billions) represents the annual local route VMT.

Table 5.20 Local route VMT Forecast by Cluster Group

	Cluster Group VMT (billions)								City and County Roads VMT (billions)		
Year	#1	#2	#3	#4	#5	#6	#7	#8	Low	Med.	High
2009	5.01	2.02	3.39	2.40	2.99	6.50	3.99	8.87	35.42	35.15	34.89
2010	5.04	2.03	3.41	2.42	3.01	6.55	4.02	8.94	35.61	35.42	35.22
2011	5.08	2.05	3.44	2.44	3.03	6.59	4.05	9.00	35.81	35.68	35.55
2012	5.12	2.06	3.47	2.46	3.05	6.64	4.08	9.07	36.01	35.95	35.88
2013	5.16	2.08	3.49	2.48	3.08	6.69	4.11	9.14	36.21	36.21	36.21
2014	5.19	2.09	3.52	2.49	3.10	6.74	4.14	9.21	36.42	36.48	36.55
2015	5.23	2.11	3.54	2.51	3.12	6.79	4.17	9.27	36.62	36.75	36.89
2016	5.27	2.12	3.57	2.53	3.15	6.84	4.20	9.34	36.82	37.02	37.23
2017	5.31	2.14	3.60	2.55	3.17	6.89	4.23	9.41	37.02	37.30	37.57
2018	5.35	2.15	3.62	2.57	3.19	6.94	4.26	9.48	37.23	37.57	37.92
2019	5.39	2.17	3.65	2.59	3.22	7.00	4.29	9.55	37.44	37.85	38.27
2020	5.43	2.19	3.68	2.61	3.24	7.05	4.32	9.62	37.64	38.13	38.63
2021	5.47	2.20	3.70	2.63	3.26	7.10	4.36	9.69	37.85	38.41	38.98
2022	5.51	2.22	3.73	2.65	3.29	7.15	4.39	9.76	38.06	38.70	39.34
2023	5.55	2.24	3.76	2.67	3.31	7.21	4.42	9.84	38.27	38.98	39.71
2024	5.59	2.25	3.79	2.68	3.34	7.26	4.45	9.91	38.49	39.27	40.07
2025	5.63	2.27	3.81	2.70	3.36	7.31	4.49	9.98	38.70	39.56	40.44
2026	5.68	2.29	3.84	2.72	3.39	7.37	4.52	10.06	38.92	39.86	40.82
2027	5.72	2.30	3.87	2.74	3.41	7.42	4.55	10.13	39.13	40.15	41.20
2028	5.76	2.32	3.90	2.77	3.44	7.48	4.59	10.21	39.35	40.45	41.58
2029	5.80	2.34	3.93	2.79	3.46	7.53	4.62	10.28	39.57	40.75	41.96
2030	5.85	2.35	3.96	2.81	3.49	7.59	4.65	10.36	39.79	41.05	42.35
2031	5.89	2.37	3.99	2.83	3.51	7.64	4.69	10.43	40.01	41.35	42.74
2032	5.93	2.39	4.02	2.85	3.54	7.70	4.72	10.51	40.23	41.66	43.14
2033	5.98	2.41	4.05	2.87	3.57	7.76	4.76	10.59	40.45	41.97	43.54
2034	6.02	2.42	4.08	2.89	3.59	7.81	4.79	10.67	40.68	42.28	43.94
2035	6.06	2.44	4.11	2.91	3.62	7.87	4.83	10.75	40.90	42.59	44.35

5.3 Estimated Statewide VMT (Non-Traffic Methods)

This section contains the results from the non-link-level methods of VMT estimation. These results are briefly discussed for each method and a summary of the aggregations from all the methods is provided in Subsection 5.3.2. These values represent a statewide annual estimate, with most estimates applicable to all vehicle classes with further disaggregation not possible. The exception is some socioeconomic travel surveys which represent only personal (non-commercial) vehicles.

One of the main objectives of this study is to reconcile the non-traffic methods with the benchmark from the selected link-level method. To gauge the extent of the errors associated with each method, a discussion of percent deviations is provided in Section 5.3.2, and the quantifiable limitations of the non-traffic approach for statewide VMT estimation are identified as well.

5.3.1 Aggregation by Estimation Method

The results based on the fuel-revenue method are shown in Table 5.21 to Table 5.23, with varying assumptions affecting estimation results. Table 5.21 assumes that the fuel is distributed to all vehicle classes with a disaggregate approach. For example, based on the distribution of diesel and gasoline vehicles, each vehicle class shows the gallonage for both diesel and fuel, with around 99% of automobiles running on gasoline. Table 5.22 assumes that the fuel is distributed with an aggregate approach. For example, vehicle classes 1-3 all run on gasoline and classes 4-13 all run on diesel. This is expected to be less accurate than a disaggregate approach. Finally, Table 5.23 shows the results when using a different traffic distribution, specifically the FHWA distribution.

All the fuel revenue-based results were similar to the statewide totals ranging from 70 to 76 billion annually, with gasoline-powered vehicles contributing around 61 to 67 billion of the statewide total VMT.

Table 5.21 Fuel distributed disaggregate by vehicle class (link-level vehicle distr.)

	Motor Fuel Revenues and Taxes			**Reported Motor Fuel Consumption**		
	Disaggregate by Vehicle Classes (Link-Level Distribution)					
Year	Gasoline	Diesel	Total	Gasoline	Diesel	Total
2009	64.336	6.897	71.232	64.553	9.085	73.637
2010	64.373	6.987	71.360	65.756	8.869	74.625
2011	65.257	8.902	74.159	63.417	10.987	74.404
2012	63.506	7.920	71.425	61.794	9.220	71.014
2013	62.902	7.311	70.212	64.546	10.303	74.849

Table 5.22 Fuel distributed aggregate by vehicle class (link-level vehicle distr.)

	Motor Fuel Revenues and Taxes			**Reported Motor Fuel Consumption**		
	Aggregate by Vehicle Classes (Link-Level Distribution)					
Year	Gasoline	Diesel	Total	Gasoline	Diesel	Total
2009	65.082	7.703	72.785	65.301	9.084	74.386
2010	65.297	6.394	71.691	67.320	7.541	74.861
2011	66.695	8.100	74.795	65.460	9.552	75.012
2012	65.211	6.537	71.748	63.516	7.709	71.225
2013	64.032	6.537	70.568	67.314	7.709	75.023

Table 5.23 Fuel distributed aggregate by vehicle class (FHWA vehicle distr.)

	Motor Fuel Revenues and Taxes			**Reported Motor Fuel Consumption**		
	Aggregate by Vehicle Classes (FHWA Distribution)					
Year	Gasoline	Diesel	Total	Gasoline	Diesel	Total
2009	66.068	6.740	72.808	66.102	7.948	74.050
2010	66.131	6.295	72.425	68.162	7.423	75.585
2011	67.445	6.764	74.209	67.445	6.764	74.209
2012	65.372	6.322	71.694	63.670	7.455	71.126
2013	64.209	6.322	70.531	67.443	7.455	74.899

These results are presented graphically in Figure 5.12 and Figure 5.13 for the fuel-revenue based approaches. Consistent estimates were obtained for 2009 to 2013, with 2012 showing lower estimates of total annual VMT.

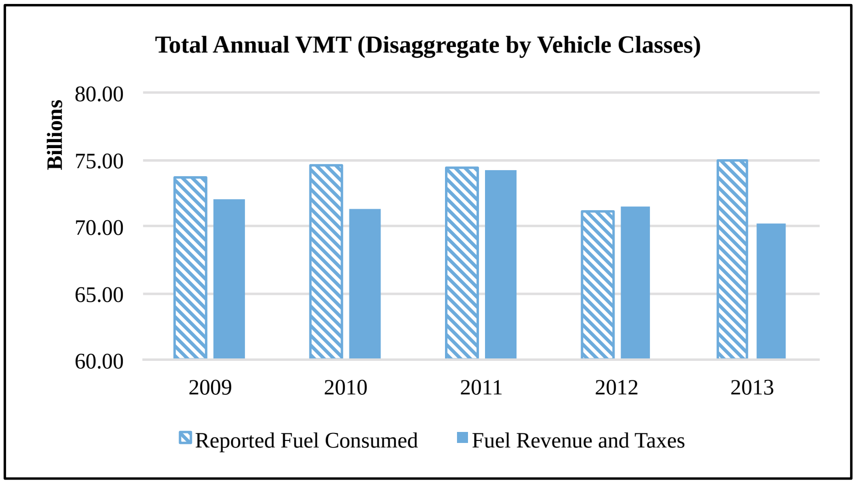

Figure 5.12 Disaggregate fuel consumption VMT estimate

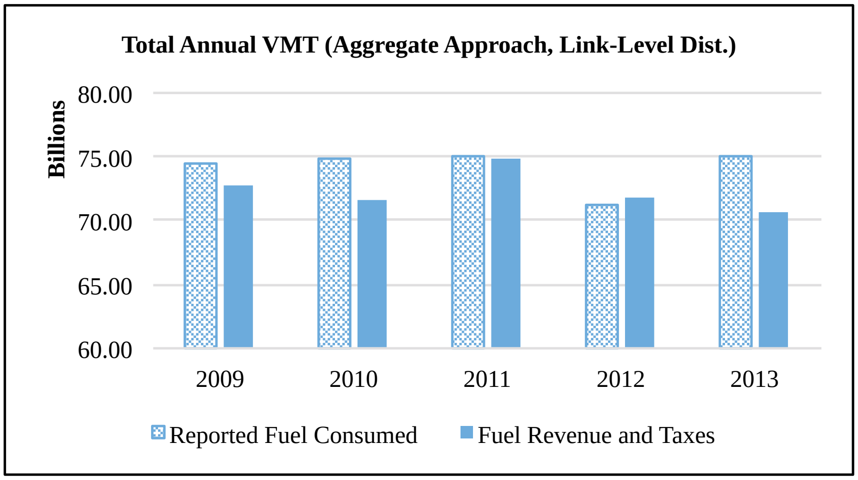

Figure 5.13 Aggregate fuel consumption VMT estimate

The statewide VMT results based on licensed drivers and demographics surveys are shown for 2009 to 2013 in Table 5.24 and graphically in Figure 5.14. The annual VMT by age group was aggregated for a state total and ranged from 73.189 billion (2009) to 78.208 billion (2013). Irrespective of the sample used, the bell-shaped curve for the distribution of VMT by age groups is shown in Figure 5.14. The highest VMT was attribute to ages 25 to 55, which was expected because that age group comprises drivers in the workforce who make more business trips annually. Ages 16 to 19 contributed the least to the statewide VMT at around 1 billion, and ages 70 and over contribute 4-5 billion to the statewide VMT.

Table 5.24 VMT by licensed drivers age groups for surrounding states

Annual VMT by Age Group	2009	2010	2011	2012	2013
16-19	1.310	1.010	0.756	1.144	1.098
20-24	4.809	4.988	5.165	2.762	4.619
25-29	6.948	7.848	8.684	6.627	7.823
30-34	8.463	8.808	9.175	8.776	9.148
35-39	7.784	7.599	7.476	7.932	8.002
40-44	8.119	8.103	8.143	8.897	8.638
45-49	9.540	9.188	8.931	9.688	9.705
50-54	7.293	7.398	7.533	8.091	7.873
55-59	5.906	6.220	6.524	6.973	6.653
60-64	4.921	5.309	5.674	5.887	5.657
65-69	3.261	3.624	3.950	4.043	3.863
70-74	1.842	1.989	2.128	2.266	2.135
75 and over	2.994	2.656	2.370	3.506	2.994
State Total	73.189	74.739	76.510	76.593	78.208

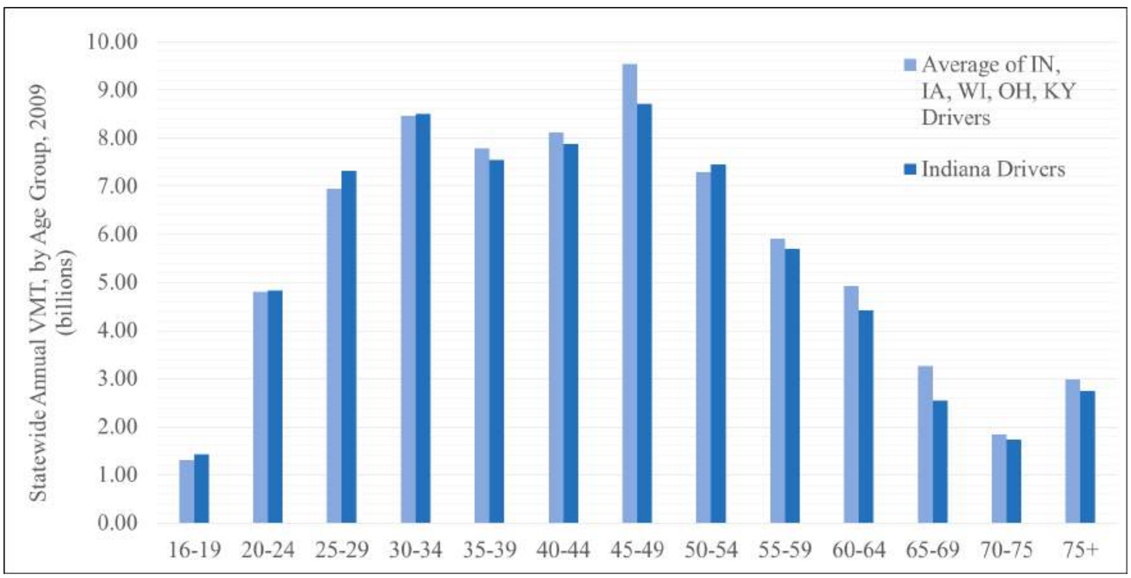

Figure 5.14 Statewide VMT by age group of licensed drivers

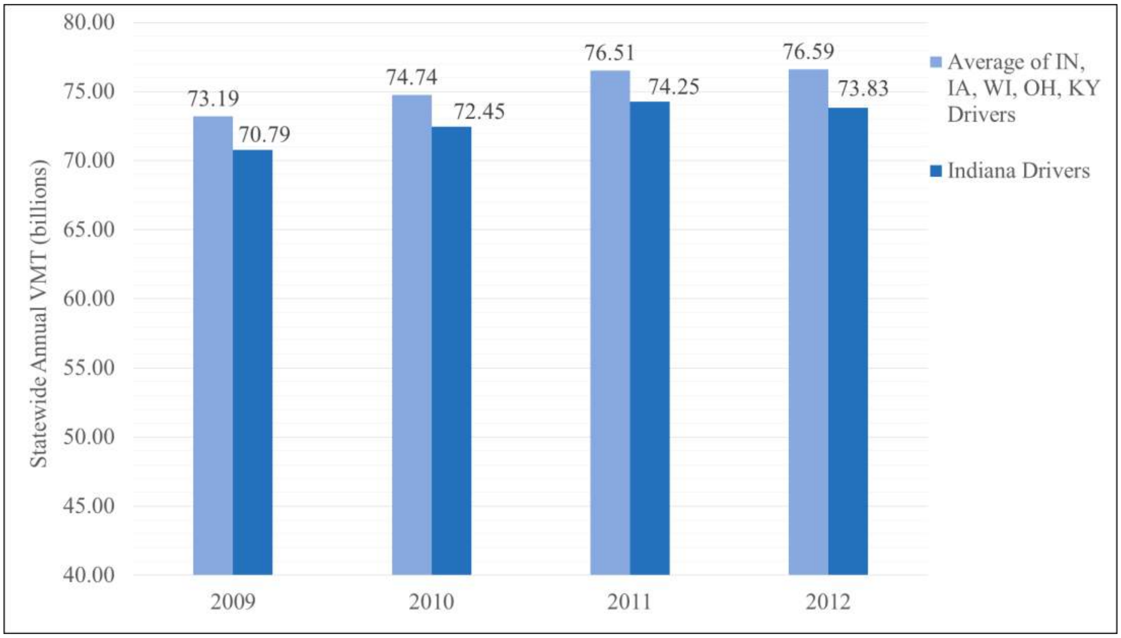

Figure 5.15 Statewide VMT for varying licensed drivers samples

An analysis of the varying licensed drivers sample (Figure 5.15) showed that the average of IN, IA, WI, OH, and KY drivers produces a higher statewide VMT of 73.19 to 76.59 billion, compared to that of the Indiana sample from 70.79 to 74.25 billion. This shows how a different annual mileage obtained from travel surveys can greatly affect the obtained statewide results.

Using vehicle registration data obtained from the BMV and classified by gross vehicle weight (BMV, 2015), the statewide VMT is estimated. An example of the 2011 annual VMT for the eight weight categories is shown in Table 5.25. Motorcycles and passenger cars comprised the majority at 51.411 billion and light-duty trucks at 14.093 billion. Overall, for all vehicles, a statewide VMT of 69.751 billion was obtained.

Table 5.25 Statewide VMT by gross vehicle weight category

Annual VMT from Vehicle Registration (2011)		
Units of Billions		
Gross Weight Category 1	Motorcycles and Passenger Cars	51.411
Gross Weight Category 2	Light-Duty Trucks	14.093
Gross Weight Category 3	Trucks 11-16K lbs	0.808
Gross Weight Category 4	Trucks 16-20Klbs and School Buses	0.112
Gross Weight Category 5	RVs, Recovery Vehicles and Other	0.921
Gross Weight Category 6	Minibuses and Trucks 20-26K lbs	0.247
Gross Weight Category 7	City/ Commercial Buses, Trucks over 26K lbs	1.264
Gross Weight Category 8	Long-Haul Commercial Trucks	0.895
All Vehicles		69.751

Based on socioeconomic regression models, the statewide VMT for the predicted and the actual economic conditions was assessed, as shown in Table 5.26 and Table 5.27, respectively. The predicted economic conditions are reflected in a higher statewide VMT than that of the actual economic conditions. For example, based on predicted economic inputs, the VMT ranges from 78.513 to 81.423 billion and from actual economic inputs, VMT ranges from 67.080 to 79.988 billion over the analysis period of 2009 to 2013. The predicted economic model does not fully account for the economic downtown, with VMT stabilizing from both approaches for 2012 and 2013. Regardless of whether the actual or predicted conditions were used, the vehicle class proportions remained relatively unchanged.

Table 5.26 Statewide VMT from predicted economic conditions

VMT Estimates based on Predicted Economic Conditions (units in billions)					
Statewide Annual VMT by Vehicle Classes	**2009**	**2010**	**2011**	**2012**	**2013**
Class 1 (Motorcycle), VMT	0.451	0.466	0.480	0.495	0.509
Class 2 (Automobile), VMT	51.091	51.224	51.357	51.490	51.623
Class 3 (Light-duty trucks), VMT	17.266	17.810	18.349	18.884	19.414
Class 4 (Buses), VMT	0.006	0.006	0.006	0.005	0.005
Classes 5-8 (Single-unit trucks), VMT	2.439	2.444	2.449	2.454	2.459
Classes 9-13 (Multi-unit trucks), VMT	7.260	7.299	7.339	7.378	7.417
Classes 1-13 (All Vehicles) VMT	**78.513**	**79.249**	**79.979**	**80.706**	**81.428**

Table 5.27 Statewide VMT from actual economic conditions

VMT Estimates based on Actual Economic Conditions (units in billions)					
Statewide Annual VMT by Vehicle Classes	**2009**	**2010**	**2011**	**2012**	**2013**
Class 1 (Motorcycle), VMT	0.514	0.531	0.546	0.556	0.569
Class 2 (Automobile), VMT	49.060	49.325	50.139	50.850	51.390
Class 3 (Light-duty trucks), VMT	8.325	9.562	13.227	16.269	18.480
Class 4 (Buses), VMT	0.006	0.006	0.006	0.006	0.005
Classes 5-8 (Single-unit trucks), VMT	2.364	2.374	2.404	2.430	2.450
Classes 9-13 (Multi-unit trucks), VMT	6.810	6.912	6.992	7.096	7.093
Classes 1-13 (All Vehicles) VMT	**67.080**	**68.710**	**73.315**	**77.207**	**79.988**

This trend toward stabilization as the analysis period progresses is evident in Figure 5.16 for statewide VMT and in Figure 5.17 for automobile VMT, where dark shading in both cases represents the actual economic conditions. The year 2016 represents a predicted future year using both of the identified socioeconomic regression models techniques. Economic downturns affect the amount of personal and commercial travel and thus can be measured as VMT. Caution is advised when using models based heavily on economic conditions, such as incomes and GDP as there is a tendency to misrepresent VMT for unforeseen changes in the economic climate.

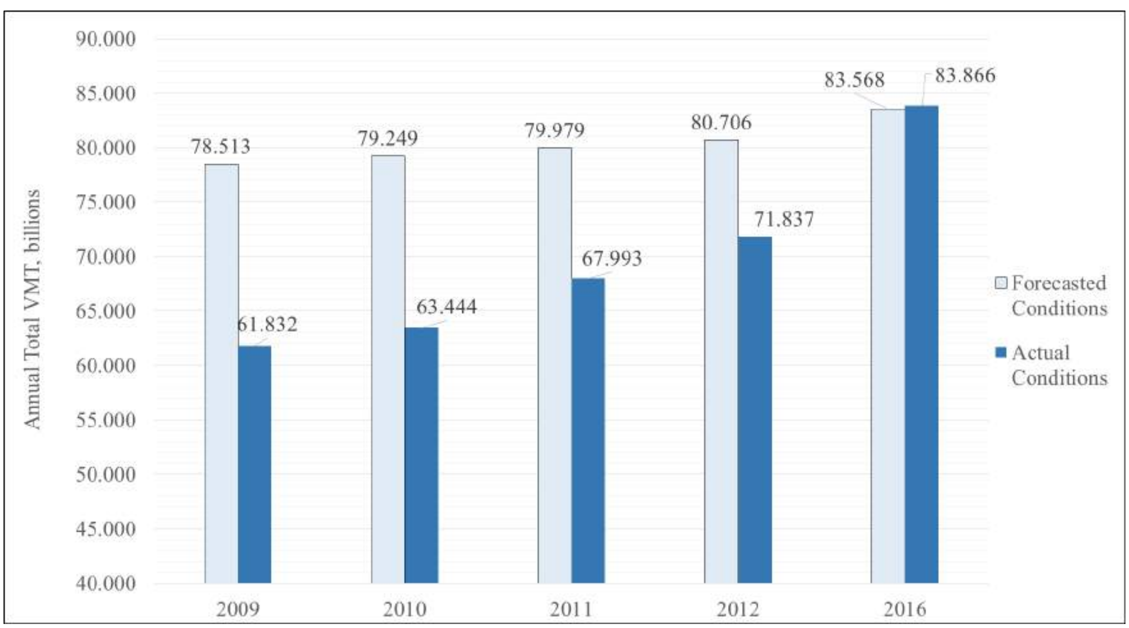

Figure 5.16 Statewide VMT estimate for varying economic conditions

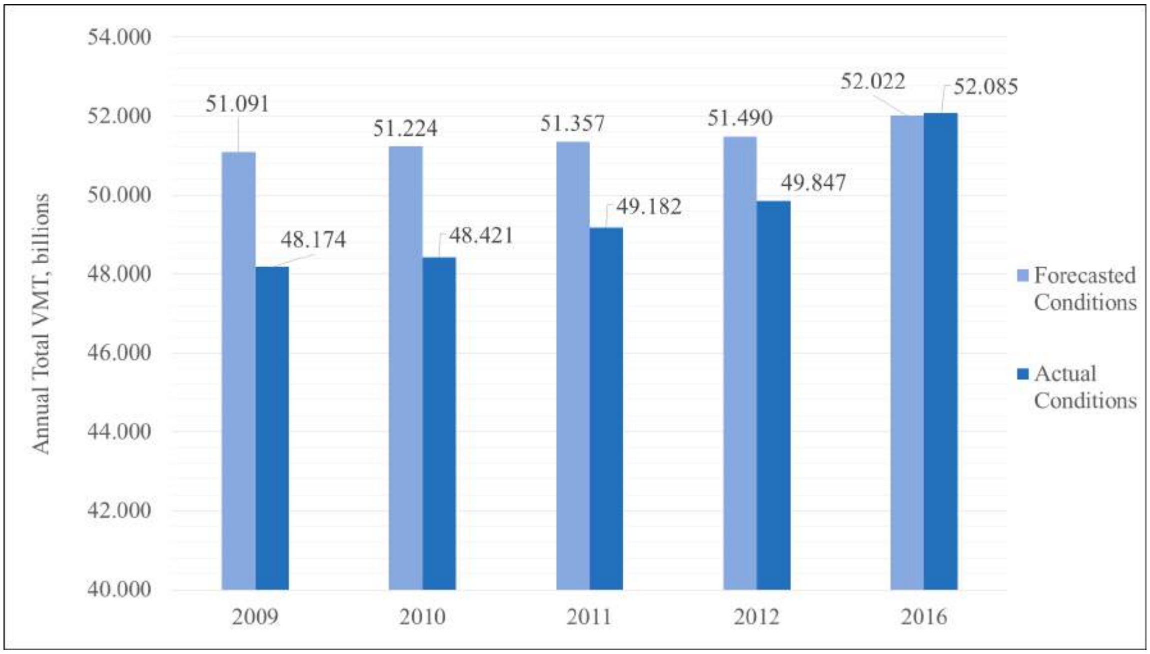

Figure 5.17 Automobile VMT estimate for varying economic conditions

Based on socioeconomic travel surveys, personal VMT (non-commercial) was estimated by land-areas and household income groups. The findings are shown in Table 5.28, with the results in billions and applicable for 2009. For all income groups, the land-area VMT are as follows: dense urban, 8.073 billion; light urban, 12.185 billion; and rural, 32.211 billion. A total of 52.469 billion VMT therefore were estimated for vehicle classes one to three.

Table 5.28 Personal VMT by household income and land-area

Personal VMT by Household Income and Land-Area	**Dense Urban**	**Light Urban**	**Rural**	**All**
Less than $20,000	1.144	0.916	2.046	4.106
$20,000 to $39,999	2.616	2.115	6.807	11.538
$40,000 to $59,999	1.780	2.473	7.397	11.650
$60,000 to $79,999	0.945	2.352	6.910	10.207
$80,000 to $99,999	0.589	1.677	3.297	5.563
Over $100,000	0.999	2.654	5.753	9.405
All	8.073	12.185	32.211	52.469

Based on the trend analysis and growth factor approaches, the predictive capabilities of different functional forms were investigated. The reported or "actual" VMT were used for validating the functional forms. Growth factors obtain a statewide VMT of 74.601 billion (2009) to 80.844 billion (2013), as presented in Table 5.29.

Table 5.29 Summary of predicted statewide VMT from trend analysis

Analysis Years	Linear Trend	Polynomial Trend	Growth Curve Model	S-Curve Trend	Growth Factors	Reported ("Actual")
2009	79.056	72.180	79.848	74.124	74.601	77.517
2010	80.098	75.220	81.100	74.129	76.116	72.357
2011	81.140	78.260	82.372	74.132	77.660	77.456
2012	82.182	81.300	83.663	74.133	79.236	78.646
2013	83.224	84.340	84.975	74.134	80.844	79.363

5.3.2 Reconciliation of Non-Traffic Methods

A summary of the approaches within each analyzed estimation method is provided in Table 5.30, with codes used to identify each method's different approaches and assumptions. These codes are referenced later in this section. The coverage level is indicated as well with the majority of the methods capable of representing statewide VMT and socioeconomic travel surveys representing the personal component of statewide VMT. The link-specific method (LS-1 and LS-2) is the study's selected method and the benchmark for comparison of the identified non-link-level estimation methods.

Table 5.30 Summary of estimation approaches within methods

Method	Code	Specific Approach and Assumptions	Coverage
Fuel-Revenue	F-1	Fuel distributed with *disaggregate* approach; gallonage from *EIA estimates*	Statewide
Fuel-Revenue	F-2	Fuel distributed with *disaggregate* approach; gallonage from *tax revenues*	Statewide
Fuel-Revenue	F-3	Fuel distributed with *aggregate* approach; galloange from *EIA estimates*	Statewide
Fuel-Revenue	F-4	Fuel distributed with *aggregate* approach; gallonage from *tax revenues*	Statewide
Fuel-Revenue	F-5	Fuel distributed with *aggregate* approach; gallonage from *EIA estimates* (FHWA distr.)	Statewide
Fuel-Revenue	F-6	Fuel distributed with *aggregate* approach; gallonage from *tax revenues* (FHWA distr.)	Statewide
Socioeconomic Regression	SE-1	Actual economic conditions as model inputs	Statewide
Socioeconomic Regression	SE-2	Predicted economic conditions as model inputs	Statewide
Vehicle Registrations	VR-1	Higher estimate of annual passenger automobile mileage	Statewide
Vehicle Registrations	VR-2	Lowest estimate of annual passenger automobile mileage	Statewide
Socioeconomic Travel Surveys	STS-1	Sample of households in Indiana	Statewide (Personal)
Socioeconomic Travel Surveys	STS-2	Sample of households in neighboring states (IN, KY, OH, WI, IA)	Statewide (Personal)
Licensed Drivers Surveys	LDD-1	Sample of households in Indiana	Statewide
Licensed Drivers Surveys	LDD-2	Sample of households in neighboring states (IN, KY, OH, WI, IA)	Statewide
HPMS	HPMS-1	Reported from the HPMS for all functional classes (AADT sampling)	Statewide
Trend Analysis	TA-1	Linear trend functional form	Statewide
Trend Analysis	TA-2	Polynomial trend functional form	Statewide
Trend Analysis	TA-3	Growth curve model functional form	Statewide
Trend Analysis	TA-4	S-curve trend functional form	Statewide
Trend Analysis	TA-5	Growth factors approach (without regression or curve fitting)	Statewide
Link-Specific	LS-1	Link-specific method for state and local routes	Statewide
Link-Specific	LS-2	Link-specific method for state and local routes	Statewide (Personal)

Based on all the estimation methods, a summary of the estimated statewide VMT values is given in Table 5.31. The four to five-year average is used for discussion and later a comparison of the percent deviations from the benchmark. LS-1, the link-specific benchmark, is 76.052 billion, and LS-2, the link-specific benchmark for non-commercial component, is 65.689 billion.

The range of statewide AVMT (total) is from 61.802 billion to 82.393 billion, based on a four or five-year average, depending on the estimation method. As observed, this nearly 20 billion range hinders the applications for business units because of the relatively poor reliability and accuracy of the obtained VMT estimates.

Table 5.31 Summary of statewide VMT results by estimation approach

Annual VMT Estimates (Units of Billions)							
Code	**Estimation Methodology**	**2009**	**2010**	**2011**	**2012**	**2013**	**4-5 Year Average**
F-1	Fuel-Revenue	73.637	74.625	74.404	71.014	74.849	73.706
F-2	Fuel-Revenue	71.232	71.360	74.159	71.425	70.212	71.678
F-3	Fuel-Revenue	74.386	74.861	75.012	71.225	75.023	74.101
F-4	Fuel-Revenue	72.785	71.691	74.795	71.748	70.568	72.318
F-5	Fuel-Revenue	74.050	75.585	74.209	71.126	74.899	73.974
F-6	Fuel-Revenue	72.808	72.425	74.209	71.694	70.531	72.333
SE-1	Socioeconomic Regression	67.080	68.710	73.315	77.207	79.988	73.260
SE-2	Socioeconomic Regression	78.513	79.249	79.979	80.706	81.428	79.975
VR-1	Vehicle Registrations	N/A	69.260	69.751	70.625	71.322	70.239
VR-2	Vehicle Registrations	N/A	60.986	61.386	62.129	62.707	61.802
STS-1	Socioeconomic Travel Surveys	52.469	53.256	54.055	54.865	55.688	53.661
STS-2	Socioeconomic Travel Surveys	51.587	52.361	53.146	53.944	54.753	52.760
LDD-1	Licensed Drivers/ Demographics	70.786	72.451	74.245	73.831	N/A	72.828
LDD-2	Licensed Drivers/ Demographics	73.189	74.739	76.510	76.593	N/A	75.258
HPMS-1	HPMS	76.628	75.761	76.485	78.923	78.311	77.222
TA-1	Trend Analysis	79.056	80.098	81.140	82.182	83.224	81.140
TA-2	Trend Analysis	72.180	75.220	78.260	81.300	84.340	78.260
TA-3	Trend Analysis	79.848	81.100	82.372	83.663	84.975	82.392
TA-4	Trend Analysis	74.124	74.129	74.132	74.133	74.134	74.130
TA-5	Trend Analysis	74.601	76.116	77.660	79.236	80.844	77.692
LS-1	Link-Specific (Benchmark)	75.313	75.375	76.393	76.353	76.825	76.052
LS-2	Link-Specific (Benchmark)	65.689	65.711	68.686	67.356	67.712	65.689

The percent deviations from the link-level benchmark are given in Table 5.32. These deviations can be thought of as adjustment factors from the “actual” or ground-truth control based on an extensive traffic-data approach. Negative percent deviations indicate that the obtained results are an underestimate, whereas a positive sign indicates that the result is an overestimate. As seen from Table 5.32, the majority of the percent deviations are an underestimate, with vehicle registrations and socioeconomic travel surveys having the most discrepancy. Vehicle registrations are underestimated by -18.7% to -7.6%. Socioeconomic travel surveys are underestimated by -19.3% to -20.7%. Trend analysis techniques can produce both under and over-estimates of statewide VMT, but are more precise with a range of -2.5% to 8.3%. Fuel revenue-based approaches under-estimate the VMT, within a more precise range of -5.8% to -2.6%. The licensed drivers and demographics approach is close to the actual with an underestimate of -4.2% to -1.0%. The HPMS is close to the benchmark, with an overestimate of 1.5%. Finally, socioeconomic regression models under and over-estimate but are close to the benchmark with percent deviations of -3.7% to 5.2%.

Table 5.32 Percent deviations from link-level benchmark by VMT estimation method

Code	Estimation Methodology	2009 (% Dev)	2010 (% Dev)	2011 (% Dev)	2012 (% Dev)	2013 (% Dev)	4-5 Year (% Dev)
F-1	Fuel-Revenue	-2.2%	-1.0%	-2.6%	-7.0%	-2.6%	-3.1%
F-2	Fuel-Revenue	-5.4%	-5.3%	-2.9%	-6.5%	-8.6%	-5.8%
F-3	Fuel-Revenue	-1.2%	-0.7%	-1.8%	-6.7%	-2.3%	-2.6%
F-4	Fuel-Revenue	-3.4%	-4.9%	-2.1%	-6.0%	-8.1%	-4.9%
F-5	Fuel-Revenue	-1.7%	0.3%	-2.9%	-6.8%	-2.5%	-2.7%
F-6	Fuel-Revenue	-3.3%	-3.9%	-2.9%	-6.1%	-8.2%	-4.9%
SE-1	Socioeconomic Regression	-10.9%	-8.8%	-4.0%	1.1%	4.1%	-3.7%
SE-2	Socioeconomic Regression	4.2%	5.1%	4.7%	5.7%	6.0%	5.2%
VR-1	Vehicle Registrations	N/A	-8.1%	-8.7%	-7.5%	-7.2%	-7.6%
VR-2	Vehicle Registrations	N/A	-19.1%	-19.6%	-18.6%	-18.4%	-18.7%
STS-1	Socioeconomic Travel Surveys	-20.1%	-19.0%	-21.3%	-18.5%	-17.8%	-19.3%
STS-2	Socioeconomic Travel Surveys	-21.5%	-20.3%	-22.6%	-19.9%	-19.1%	-20.7%
LDD-1	Licensed Drivers/ Demographics	-6.0%	-3.9%	-2.8%	-3.3%	N/A	-4.2%
LDD-2	Licensed Drivers/ Demographics	-2.8%	-0.8%	0.2%	0.3%	N/A	-1.0%
HPMS-1	HPMS	1.7%	0.5%	0.1%	3.4%	1.9%	1.5%
TA-1	Trend Analysis	5.0%	6.3%	6.2%	7.6%	8.3%	6.7%
TA-2	Trend Analysis	-4.2%	-0.2%	2.4%	6.5%	9.8%	2.9%
TA-3	Trend Analysis	6.0%	7.6%	7.8%	9.6%	10.6%	8.3%
TA-4	Trend Analysis	-1.6%	-1.7%	-3.0%	-2.9%	-3.5%	-2.5%
TA-5	Trend Analysis	-0.9%	1.0%	1.7%	3.8%	5.2%	2.2%

These adjustment factors, from the solid black line indicated as the benchmark VMT estimation method (segment-level), are graphically presented in Figure 5.18. For example, the percentage represents the extent of deviation from the actual VMT from each VMT estimation method. Trend analysis techniques both over and underestimate within a +/-10% range. Similar findings for all the investigated methods of VMT estimation are provided in Figure 5.18.

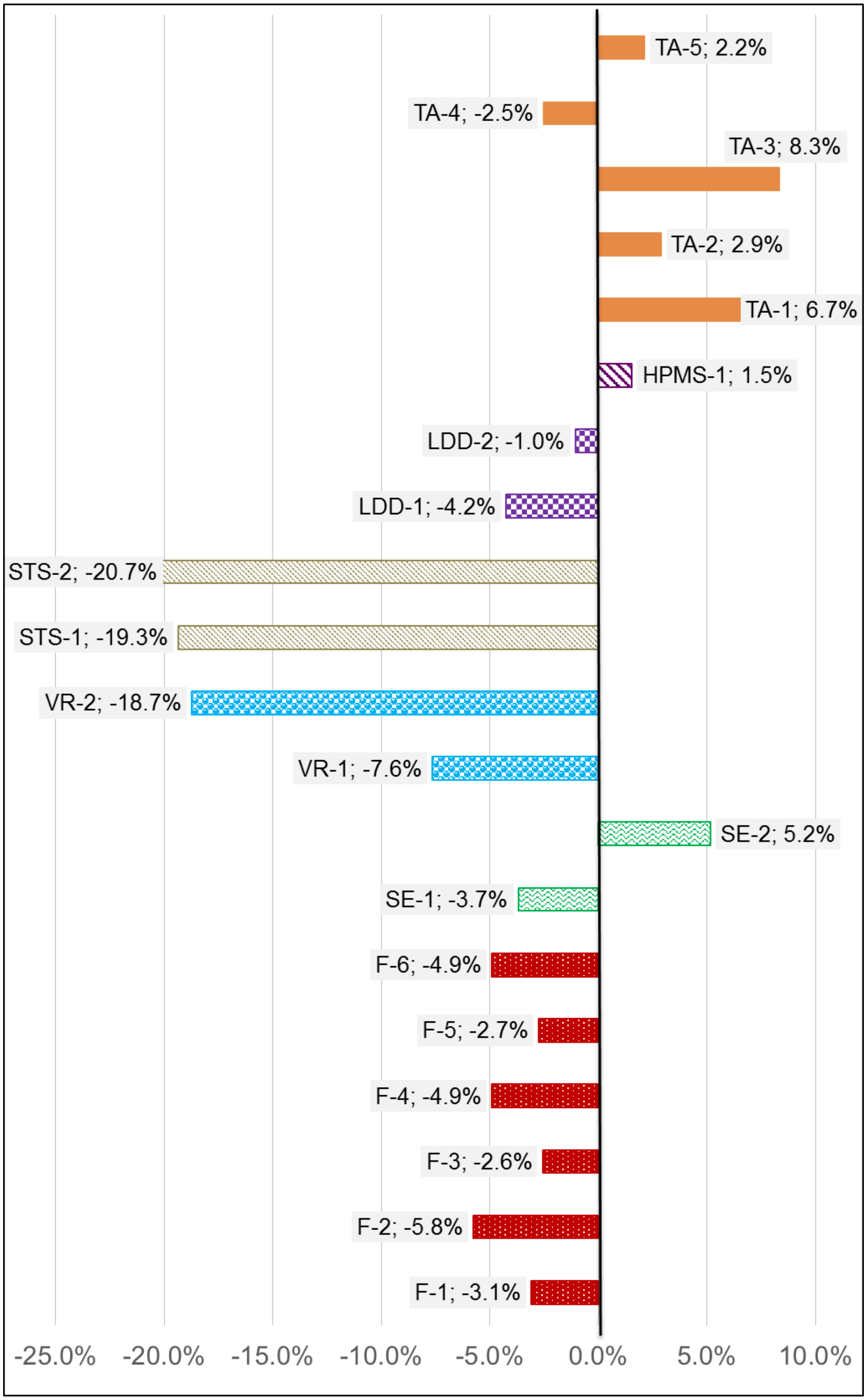

Figure 5.18 Comparison of percent deviations by VMT estimation method
(refer to Table 5.30 for codes)

5.4 Chapter Summary

This chapter provided the results from statewide VMT estimations at the link level, aggregated over varying geographical and analysis scopes. Aggregations based on available link-level traffic data were provided by county, administrative district, road designation, economic region, and HPMS. In addition, predicted statewide VMT at the link level was provided for future years. Coverage for statewide, route, vehicle class, and road designation was provided for the statewide VMT estimates. Finally, the results from the non-link-level methods (non-traffic based) of VMT estimation were discussed.

The findings indicated significant variations among the estimation methods and approaches within those methods, based on a comparison of the obtained estimates to the link-level benchmark adopted for this study. Overall, commercial VMT is underrepresented by non-traffic based VMT estimation methods and may contribute to the trend of underestimating statewide VMT.

CHAPTER 6. SUMMARY AND CONCLUSIONS

6.1 Summary

This section provides a summary of the study's motivation, problem statement, and framework developed for statewide VMT estimation and key numerical findings for different methods and the link-level (benchmark) method selected to reconcile estimates and to provide for future VMT estimation.

6.1.1 Summary of the Problem Statement and Motivation

The primary purpose of this research was to improve the consistency, reliability, and accuracy of VMT estimates at present and future times for INDOT by developing a consistent framework intended for VMT estimation at the various divisions and hierarchical levels of INDOT. Such a need is underscored by the realization that VMT estimates play a critical role in INDOT's various functions and business processes. For example, with declining highway revenue from fuel taxes and the subsequent imminent move to VMT-based user fees, the need for reliable VMT estimates is critical. Also, VMT data are useful inputs in the evaluation of the Indiana highway network (or parts thereof) on the basis of different highway performance criteria, including crash and mobility performance at the overall network level. Furthermore, VMT data are reported annually to federal oversight agencies. Other end applications include highway revenue forecasting, traffic and energy impact assessments, and highway cost allocation. The current impaired ability of INDOT to readily produce consistent VMT estimates by functional and vehicle class hinders the several agency business processes for which VMT estimates are critical. In this regard, the lack of a central and consistent source for retrieving VMT information for specific corridors or at any level of system-wide aggregation is problematic for VMT-stakeholders.

VMT estimation methods are generally classified as traffic-based and non-traffic-based. The existing methods for VMT estimation are often non-traffic-based, that is, they do not use data on highway traffic volume; for example, in a few of these methods, VMT is estimated using data from travel surveys, fuel revenue, fleet efficiency, demographics, and socioeconomic conditions. However, the resulting VMT estimates from these methods often do not match the total aggregate VMT reported to the FHWA. Also, these methods tend to be data-intensive and require significant data processing efforts, which has proved to be worrisome, considering the multitude and critical nature of applications that require VMT estimates. On the other hand, traffic-based methods of VMT estimation use traffic volume data and section length information; however, these methods are applicable only to highway networks for which traffic data and inventory (section length) data are available. As such, traffic-based methods are typically not used for VMT estimation on local roads. Recognizing that local routes constitute a significant share of the entire road inventory in Indiana, this study looked at the local VMT in-depth to increase the reliability and accuracy of the VMT estimates for this road class.

6.1.2 Summary of the Research Framework

The first task in the research was a comprehensive review of the literature and qualitative analysis of the VMT estimation methods appropriate for different application levels. Also, a survey of the VMT stakeholders at INDOT was carried out in order to identify the challenges they face with VMT estimation and to identify the preferred outputs of any platform for VMT estimation. These first steps were undertaken to streamline the study effort, to categorize the different methods of VMT estimation, and to identify their limitations.

The non-traffic methods were deemed inadequate for meeting the entirety of INDOT’s needs because these methods do not readily provide VMT estimates at the preferred levels of aggregation, including vehicle class, functional class, route, and spatial area. Due to the inherent nature of its VMT estimation procedure, the segment-level or link-level method was selected as the best method and therefore its VMT estimates were used as the benchmark estimates not only for reconciling any inconsistencies in the VMTs estimated using the other VMT methods but also for developing quantitative calibration factors for the other methods.

The benchmark method uses the traffic counts at the segment level to provide full coverage of the road inventory. This method is implemented in a series of Excel spreadsheets, providing a platform for present and future VMT information as well as allowing for data updatability and scenario-based traffic growth analysis. Using the traffic volume data for the entire population of Indiana's state highways (interstates and US and state roads) and also a representative sample of local routes (city streets and county roads), these comprehensive databases facilitated extensive aggregations including the corridor level, region (district, county, etc.), highway class, route type, NHS class, and vehicle class. These Excel spreadsheets are accompanied by a user's manual (sample is included in Appendix B of this thesis).

To facilitate VMT prediction at a future year, growth factors were developed based on the observed traffic data. These growth factors were developed by functional class and were applied at the segment level to represent any time-horizon selected in the spreadsheet system. To better account for the stochastic nature of long-term traffic forecasting, a range of VMT estimates (low, medium, and high) were provided for each of the several levels and types of VMT aggregations, allowing for a scenario-based analysis of traffic growth to quickly assess possible future VMT conditions.

In view of the importance of spatial relationships in travel distributions, the use of spatial interpolation techniques was investigated to provide a more reliable characterization of the VMTs for the individual local roads. For local segments with unknown AADTs, the traffic counts from neighboring segments were used as a basis to spatially interpolate the AADTs and, subsequently, the VMT. Different spatial interpolation techniques within the ArcGIS software were investigated for this purpose, including kriging, natural neighbor, inverse distance weighting, and trend. Each interpolation technique produced a raster surface of the continuous variation in the AADT across each county under investigation. To assess the accuracy and appropriateness of each technique for local road VMT estimation, the techniques were validated by road class for each of the representative counties that were analyzed. Also, a county-wide total VMT was developed, thereby establishing benchmark values for future use. The capabilities of spatial interpolation were demonstrated quantitatively for the purpose of estimating the VMT of local roads in Indiana.

6.1.3 Summary of Findings across Different Methods

The results from the different non-traffic VMT estimation methods varied greatly, not only across methods, but with respect to the assumptions and specific techniques within each. This variation is illustrated in Table 6.1, for the four to five year (2009-2013) data-average, with the link level benchmark developed for this study as 76.05 billion for statewide VMT (classes 1-13) and 65.69 billion for personal VMT (classes 1-3).

Table 6.1 Summary of total VMT across different estimation methods

Annual VMT Estimates (Units of Billions)		
Code	**Estimation Methodology**	**4-5 Year Average**
F-1	Fuel-Revenue	73.706
F-2	Fuel-Revenue	71.678
F-3	Fuel-Revenue	74.101
F-4	Fuel-Revenue	72.318
F-5	Fuel-Revenue	73.974
F-6	Fuel-Revenue	72.333
SR-1	Socioeconomic Regression	73.260
SR-2	Socioeconomic Regression	79.975
VR-1	Vehicle Registrations	70.239
VR-2	Vehicle Registrations	61.802
STS-1	Socioeconomic Travel Surveys	53.661
STS-2	Socioeconomic Travel Surveys	52.760
LDD-1	Licensed Drivers/ Demographics	72.828
LDD-2	Licensed Drivers/ Demographics	75.258
HPMS-1	HPMS	77.222
TA-1	Trend Analysis	81.140
TA-2	Trend Analysis	78.260
TA-3	Trend Analysis	82.392
TA-4	Trend Analysis	74.130
TA-5	Trend Analysis	77.692
LS-1	Link-Specific (Benchmark)	76.052
LS-2	Link-Specific (Benchmark)	65.689

For example, fuel revenues and fleet efficiency yielded statewide VMT estimates in the range of 71.68 to 74.10 billion. These VMT estimates are underestimates of 1.95 to 4.37 billion, as compared to the benchmark developed in this research. The fuel-revenue method was less accurate for estimating individual vehicle class VMT and may underrepresent commercial VMT.

For socioeconomic regression models, the data and assumptions selected on economic conditions affected the results. Applying the actual economic conditions led to a value of 73.26 billion, while using the predicted economic conditions led to a higher value of 79.98 billion, indicating that VMT derived from regression techniques are susceptible to economic fluctuations and unforeseen demographic changes.

Using vehicle registrations and an assumed average annual travel per vehicle, VMT estimates of 61.80 to 70.24 billion were observed, underrepresenting statewide VMT by 5.81 to 14.25 billion.

Socioeconomic travel surveys, considering personal VMT only (classes 1-3), yielded estimates of 52.76 to 53.66 billion. These values are significant underestimates of 12.03 to 12.93 billion. Travel surveys with licensed driver and demographic data yielded estimates of 72.83 to 75.26 billion. While this method underestimates VMT by 0.79 to 3.22 billion, the inputs derived from self-reported mileage may be prone to misrepresentation and infrequent updating.

Based on the FHWA's HPMS reports, a statewide VMT estimate of 77.22 billion was determined, overestimating VMT by 1.17 billion, based on this research.

The trend analysis and growth factor method yielded a range of statewide VMT estimates, from 74.13 to 82.39 billion. Trend analysis techniques were found to both underestimate and overestimate statewide VMT, depending on the estimation approach used.

One of the limitations of most non-traffic methods is that, due to their aggregate nature, it is often not possible to develop a VMT estimate for each vehicle class. Exceptions are the fuel-revenue method (which can provide VMT by the 13-FHWA vehicle classes) and socioeconomic regression (which can provide VMT by groups of vehicle classes), as shown in Table 6.2.

Table 6.2 Summary of vehicle-class VMT across different estimation methods

Annual VMT Estimates (Units of billions)													
VMT Estimation Method	**FHWA Vehicle Class**												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Socieconomic Regression (SR-1)	0.569	51.390	18.48	0.005	2.450				7.093				
Socieconomic Regression (SR-2)	0.509	51.623	19.414	0.005	2.459				7.417				
Fuel-Revenue (F-1)	0.801	49.945	14.613	0.219	2.219	1.145	0.370	0.428	4.856	0.073	0.116	0.041	0.023
Fuel-Revenue (F-2)	0.780	48.419	14.166	0.156	1.652	0.828	0.268	0.310	3.454	0.052	0.083	0.029	0.016
Fuel-Revenue (F-3)	75.023			7.709									
Fuel-Revenue (F-6)	70.531			6.322									

To aid with reconciling the VMT values across the different methods, calibrations factors were developed based on the percent deviation for each method and technique used. In Table 6.3, the codes representing each technique are explained in Table 5.30. For example, for VMT obtained using a linear trend analysis (TA-1) such as forecasting using historical data, a calibration factor of 0.933 can be used. That is, the VMT estimate produced by the method is multiplied by 0.933 to obtain the true VMT (i.e., the VMT obtained using the benchmark method).

Table 6.3 Calibrator factor table for VMT estimation methods

Method	**Technique**	**Percent Deviation**	**Calibration Factor**
Trend Analysis	TA-1	6.70	0.933
	TA-2	2.90	0.971
	TA-3	0.30	0.997
	TA-4	-2.50	1.025
	TA-5	-3.10	1.031
	TA-6	-2.90	1.029
	TA-7	2.20	0.978
HPMS	HPMS-1	1.50	0.985
Licensed Drivers and Demographics	LDD-1	-1.00	1.010
	LDD-2	-4.20	1.042
Socioeconomic Travel Surveys	STS-1	-20.70	1.207
	STS-2	-19.30	1.193
Vehicle Registrations	VR-1	-7.60	1.076
	VR-2	-18.70	1.187
Socioeconomic Regression	SR-1	-3.70	1.037
	SR-2	5.20	0.948
Fuel-Revenue	F-1	-3.10	1.031
	F-2	-5.80	1.058
	F-3	-2.60	1.026
	F-4	-4.90	1.049
	F-5	-2.70	1.027
	F-6	-4.90	1.049

6.1.4 Summary of Findings using Link-Level Method

Table 6.4 presents an aggregation of the VMT estimates by jurisdiction, highway route type, FHWA functional class, administrative district, and commercial travel. The distributions of these key statewide VMT aggregations are visually represented in Figure 6.1. The medium range of observed traffic growth was applied for these aggregations, with the annual values provided in units of billions. Also, an average percentage of the total, for each aggregation category, was estimated for the 2015-2025 period, shown in Table 6.4.

With regard to VMT by highway categories, interstates, US highways, state highways, and local roads account for 23.3%, 13.5%, 16.9%, and 46.3%, of the total statewide VMT, respectively. Similarly, for assessing VMT by FHWA functional classes, using the distributions developed in this study based on an extensive link-level traffic sample, FC 1, FC 2, FC 3, FC 4, FC 5, FC 6, and FC 7, account for 23.3%, 2.1%, 26.2%, 19.6%, 24.9%, 1.1%, and 2.8%, respectively.

For state highway VMT by INDOT administrative districts, the results indicate that on average, Crawfordsville, Fort Wayne, Greenfield, LaPorte, Seymour, and Vincennes contain 13.2%, 14.8%, 26.2%, 20.0%, 16.3%, and 9.4%, of the state highway VMT.

Aggregations for VMT by vehicle classes for the primary highway systems of state and local routes are provided in Table 6.5 for 2015-2035. Over the analysis period, as expected, vehicle class 2 (automobiles) represents the highest VMT, with vehicle class 3, light-duty vehicles, having the second highest VMT. Class 9 trucks have the highest commercial VMT, primarily on state routes, with the combination truck VMT predominately on state routes.

Table 6.4 Summary of key VMT estimates (medium growth range)

			Annual VMT Estimates (Units of Billions)										
Aggregation	Category	Average % of Total	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
Jurisdiction	All	100.0%	78.404	79.161	79.925	80.698	81.479	82.269	83.067	83.874	84.690	85.516	86.350
	State Routes	53.7%	41.652	42.137	42.627	43.124	43.627	44.136	44.653	45.176	45.705	46.242	46.786
	Local Routes	46.3%	36.752	37.024	37.298	37.574	37.852	38.132	38.414	38.699	38.985	39.273	39.564
Highway Route Type	Interstates	23.3%	18.278	18.456	18.636	18.818	19.002	19.188	19.375	19.565	19.756	19.949	20.145
	US Highways	13.5%	10.398	10.529	10.662	10.797	10.934	11.073	11.214	11.357	11.502	11.649	11.798
	State Highways	16.9%	12.977	13.151	13.328	13.508	13.690	13.875	14.063	14.254	14.447	14.643	14.843
	Local Roads	46.3%	36.752	37.024	37.298	37.574	37.852	38.132	38.414	38.699	38.985	39.273	39.564
FHWA Functional Class	FC 1	23.3%	18.278	18.456	18.636	18.818	19.002	19.188	19.375	19.565	19.756	19.949	20.145
	FC 2	2.1%	1.629	1.648	1.668	1.688	1.709	1.729	1.750	1.771	1.792	1.814	1.836
	FC 3	26.2%	20.396	20.623	20.852	21.085	21.320	21.559	21.800	22.045	22.293	22.545	22.799
	FC 4	19.6%	15.380	15.519	15.660	15.803	15.946	16.092	16.239	16.387	16.537	16.688	16.841
	FC 5	24.9%	19.654	19.823	19.993	20.165	20.339	20.514	20.691	20.870	21.050	21.232	21.416
	FC 6	1.1%	0.844	0.851	0.858	0.865	0.873	0.880	0.888	0.895	0.903	0.910	0.918
	FC 7	2.8%	2.223	2.240	2.256	2.273	2.290	2.307	2.324	2.342	2.359	2.377	2.394
Administrative District (State Routes Only)	Crawfordsville	13.2%	5.508	5.572	5.637	5.703	5.770	5.837	5.905	5.974	6.044	6.115	6.187
	Fort Wayne	14.8%	6.174	6.246	6.318	6.392	6.467	6.542	6.619	6.696	6.775	6.854	6.935
	Greenfield	26.2%	10.909	11.036	11.164	11.294	11.426	11.560	11.695	11.832	11.970	12.111	12.253
	Laporte	20.0%	8.321	8.418	8.516	8.615	8.716	8.818	8.921	9.025	9.131	9.238	9.347
	Seymour	16.3%	6.804	6.883	6.963	7.044	7.126	7.210	7.294	7.379	7.466	7.554	7.642
	Vincennes	9.4%	3.936	3.982	4.028	4.075	4.122	4.171	4.219	4.269	4.319	4.370	4.421
Commercial	All	100.0%	9.322	9.420	9.519	9.620	9.722	9.825	9.929	10.035	10.142	10.250	10.359
	State Routes	74.9%	6.943	7.024	7.105	7.188	7.272	7.357	7.443	7.530	7.619	7.708	7.799
	Local Routes	25.1%	2.379	2.396	2.414	2.432	2.450	2.468	2.486	2.505	2.523	2.542	2.561

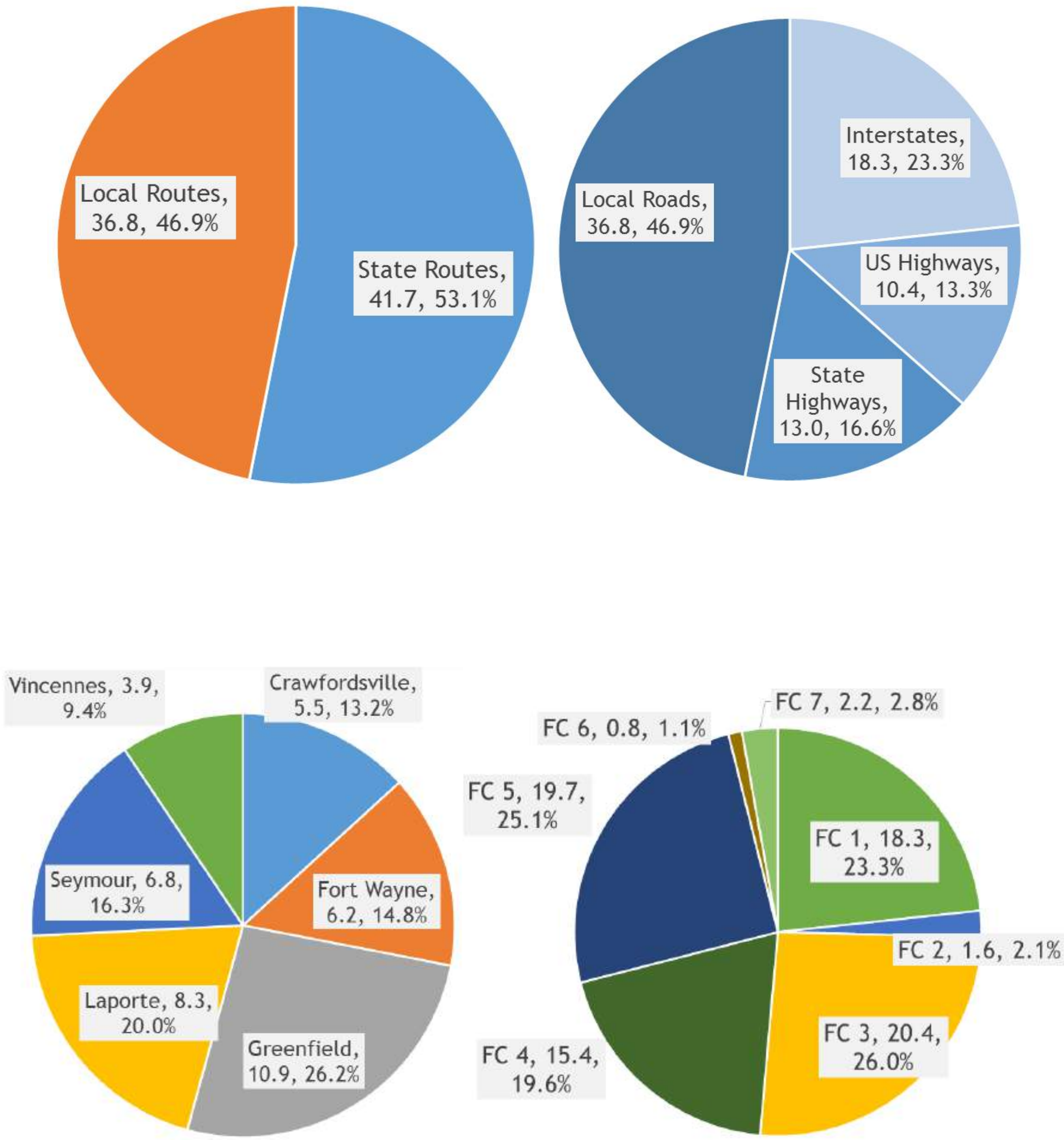

Figure 6.1 Distribution of statewide VMT by selected aggregations

Table 6.5 Summary of VMT by highway system and vehicle class (medium growth range)

FHWA Vehicle Class	Primary Highway Systems	VMT Estimates by Year (Units in Billions)																				
		2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
1	State Routes	0.209	0.211	0.214	0.216	0.219	0.221	0.224	0.226	0.229	0.232	0.234	0.237	0.240	0.243	0.246	0.249	0.252	0.255	0.258	0.261	0.264
	Local Routes	0.220	0.221	0.223	0.224	0.226	0.228	0.229	0.231	0.233	0.235	0.236	0.238	0.240	0.242	0.243	0.245	0.247	0.249	0.251	0.253	0.254
2	State Routes	25.046	25.337	25.632	25.930	26.233	26.539	26.850	27.164	27.483	27.805	28.132	28.464	28.799	29.139	29.483	29.832	30.186	30.544	30.907	31.275	31.648
	Local Routes	23.988	24.165	24.344	24.524	24.706	24.889	25.073	25.258	25.445	25.634	25.823	26.014	26.207	26.401	26.596	26.793	26.991	27.191	27.392	27.595	27.799
3	State Routes	9.455	9.565	9.676	9.789	9.903	10.019	10.136	10.255	10.375	10.497	10.620	10.745	10.872	11.001	11.131	11.262	11.396	11.531	11.668	11.807	11.948
	Local Routes	10.166	10.241	10.317	10.393	10.470	10.548	10.626	10.704	10.784	10.863	10.944	11.025	11.106	11.189	11.271	11.355	11.439	11.523	11.609	11.695	11.781
4	State Routes	0.111	0.112	0.113	0.115	0.116	0.117	0.119	0.120	0.122	0.123	0.125	0.126	0.127	0.129	0.130	0.132	0.134	0.135	0.137	0.138	0.140
	Local Routes	0.039	0.040	0.040	0.040	0.040	0.041	0.041	0.041	0.042	0.042	0.042	0.043	0.043	0.043	0.044	0.044	0.044	0.045	0.045	0.045	0.046
5	State Routes	1.355	1.370	1.386	1.402	1.419	1.435	1.452	1.469	1.486	1.504	1.521	1.539	1.558	1.576	1.595	1.613	1.633	1.652	1.672	1.691	1.712
	Local Routes	0.627	0.632	0.636	0.641	0.646	0.650	0.655	0.660	0.665	0.670	0.675	0.680	0.685	0.690	0.695	0.700	0.705	0.711	0.716	0.721	0.727
6	State Routes	0.371	0.376	0.380	0.384	0.389	0.394	0.398	0.403	0.408	0.412	0.417	0.422	0.427	0.432	0.437	0.442	0.448	0.453	0.458	0.464	0.469
	Local Routes	0.379	0.381	0.384	0.387	0.390	0.393	0.396	0.399	0.402	0.405	0.408	0.411	0.414	0.417	0.420	0.423	0.426	0.429	0.432	0.436	0.439
7	State Routes	0.105	0.106	0.108	0.109	0.110	0.112	0.113	0.114	0.116	0.117	0.118	0.120	0.121	0.122	0.124	0.125	0.127	0.128	0.130	0.131	0.133
	Local Routes	0.129	0.130	0.131	0.132	0.133	0.134	0.135	0.136	0.137	0.138	0.139	0.140	0.141	0.142	0.143	0.145	0.146	0.147	0.148	0.149	0.150
8	State Routes	0.410	0.415	0.420	0.425	0.430	0.435	0.440	0.445	0.450	0.456	0.461	0.466	0.472	0.478	0.483	0.489	0.495	0.501	0.507	0.513	0.519
	Local Routes	0.121	0.121	0.122	0.123	0.124	0.125	0.126	0.127	0.128	0.129	0.130	0.131	0.132	0.133	0.134	0.135	0.136	0.137	0.138	0.139	0.140
9	State Routes	4.338	4.389	4.440	4.492	4.544	4.597	4.651	4.705	4.761	4.817	4.873	4.931	4.989	5.048	5.107	5.168	5.229	5.291	5.354	5.418	5.482
	Local Routes	1.052	1.059	1.067	1.075	1.083	1.091	1.099	1.107	1.115	1.124	1.132	1.140	1.149	1.157	1.166	1.175	1.183	1.192	1.201	1.210	1.219
10	State Routes	0.062	0.063	0.063	0.064	0.065	0.066	0.066	0.067	0.068	0.069	0.070	0.070	0.071	0.072	0.073	0.074	0.075	0.076	0.076	0.077	0.078
	Local Routes	0.017	0.017	0.017	0.018	0.018	0.018	0.018	0.018	0.018	0.018	0.019	0.019	0.019	0.019	0.019	0.019	0.019	0.020	0.020	0.020	0.020
11	State Routes	0.115	0.116	0.118	0.119	0.120	0.122	0.123	0.125	0.126	0.128	0.129	0.131	0.132	0.134	0.135	0.137	0.138	0.140	0.142	0.143	0.145
	Local Routes	0.007	0.007	0.007	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.009
12	State Routes	0.040	0.041	0.041	0.042	0.042	0.043	0.043	0.044	0.044	0.045	0.045	0.046	0.047	0.047	0.048	0.048	0.049	0.049	0.050	0.051	0.051
	Local Routes	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002
13	State Routes	0.035	0.035	0.035	0.036	0.036	0.037	0.037	0.038	0.038	0.038	0.039	0.039	0.040	0.040	0.041	0.041	0.042	0.042	0.043	0.043	0.044
	Local Routes	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006

A visual depiction of statewide annual VMT growth, for 2009 to 2035, is shown in Figure 6.2. Three traffic growth scenarios (low, medium, and high) are provided in Figure 6.2. After 2025, the gaps between the predicted VMTs widens significantly. These long-term predictions should be used cautiously because of the influence of economic conditions and effect of changing technologies.

VMT by highway category, for interstates, US and state roads, and local roads (medium growth) is shown in Figure 6.3.

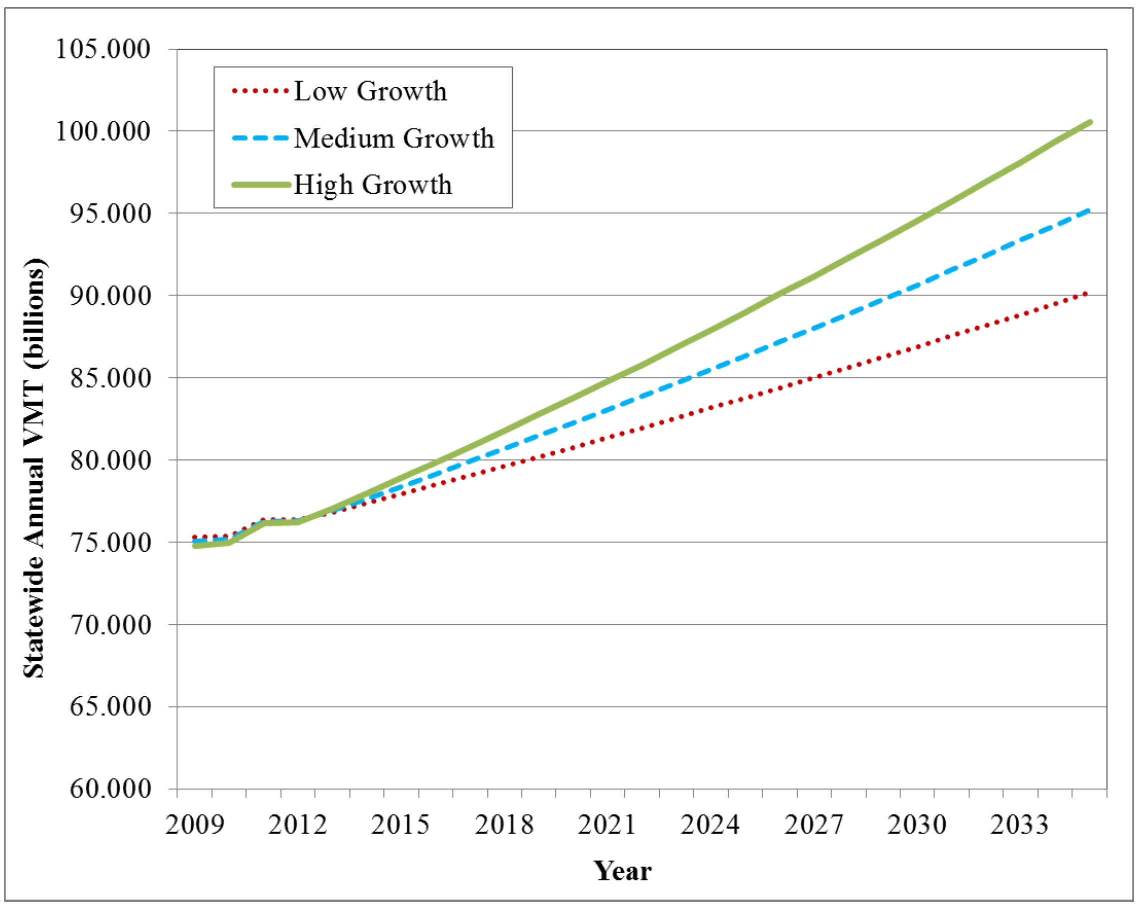

Figure 6.2 VMT growth (2009-2035) for statewide total

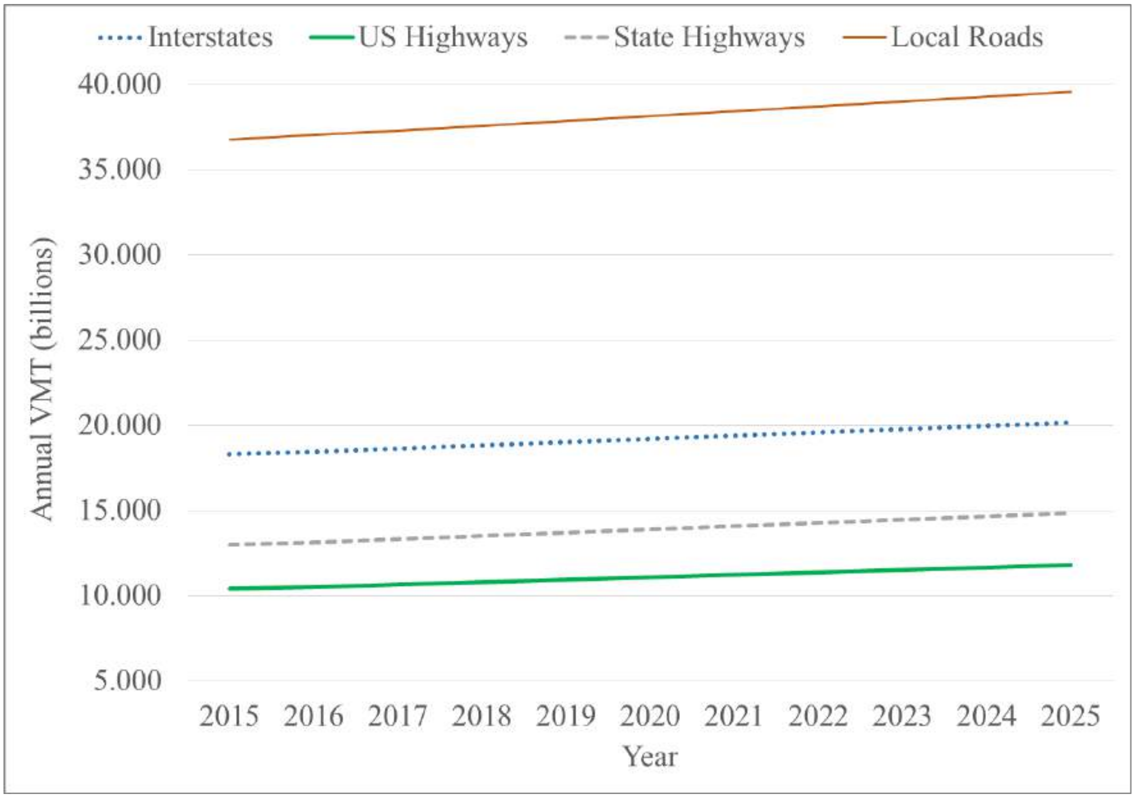

Figure 6.3 VMT growth (2015-2025) by highway jurisdiction and class

A visual assessment of the VMT growth scenarios by FHWA vehicle class is provided in Figure 6.4 to Figure 6.10. Estimates from 2015 to 2035 are provided, with the low VMT range more closely aligning with growth factors derived from INDOT's annual adjustment factors (INDOT, 2014).

Class 1 to 3 vehicles are primarily non-commercial and class 4 to 13 vehicles are primarily commercial. The widest gap in the prediction range was observed for vehicle class 2 (automobiles). Note that the y-axis represents annual VMT in billions and does not start at zero for any of the VMT estimate plots, except for vehicle class.

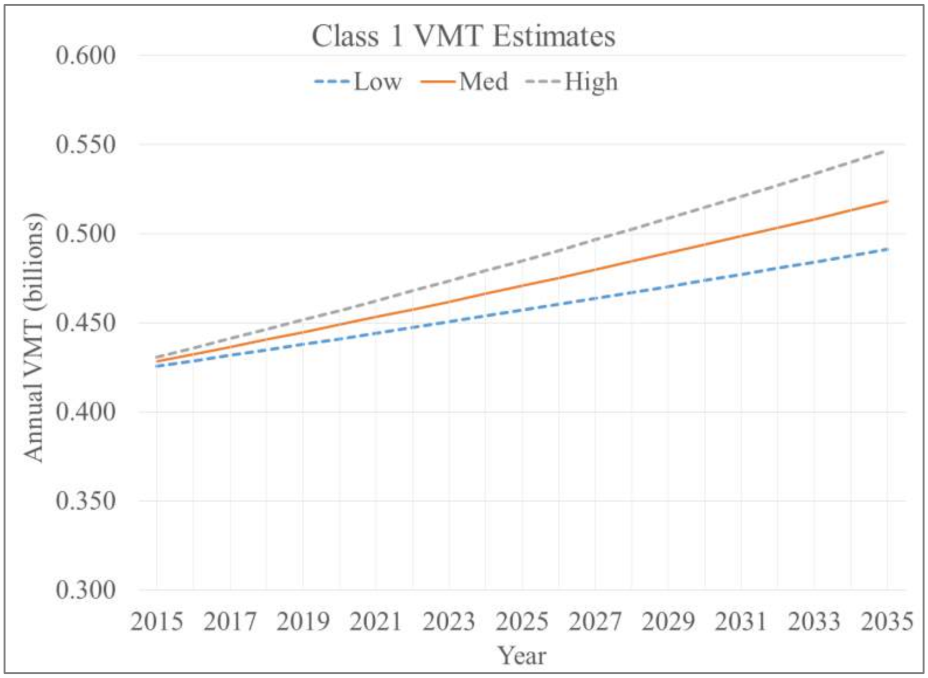

Figure 6.4 VMT growth (2015-2035) for class 1 vehicles

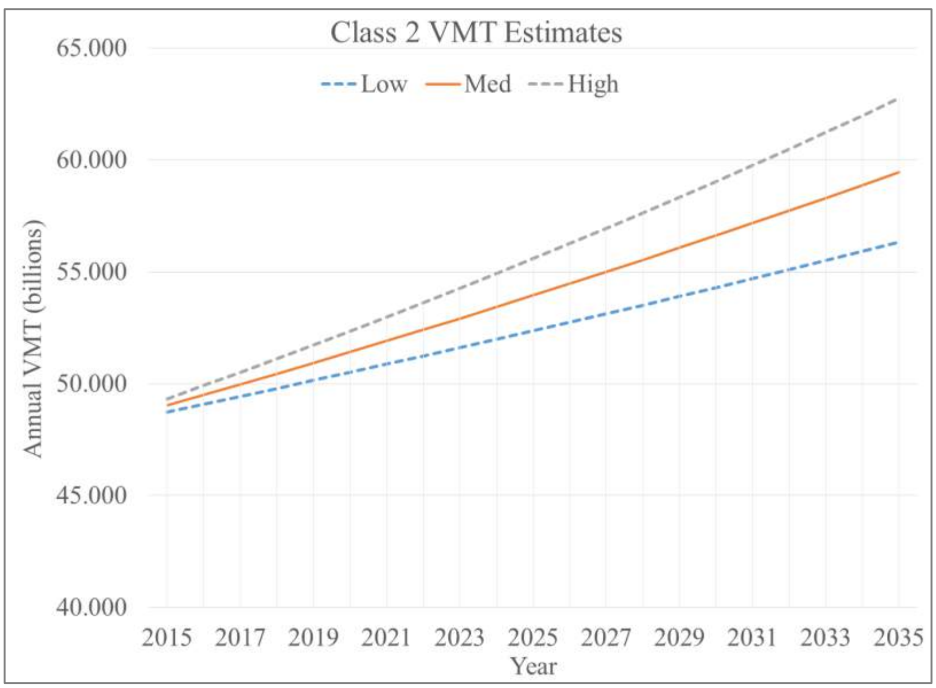

Figure 6.5 VMT growth (2015-2035) for class 2 vehicles

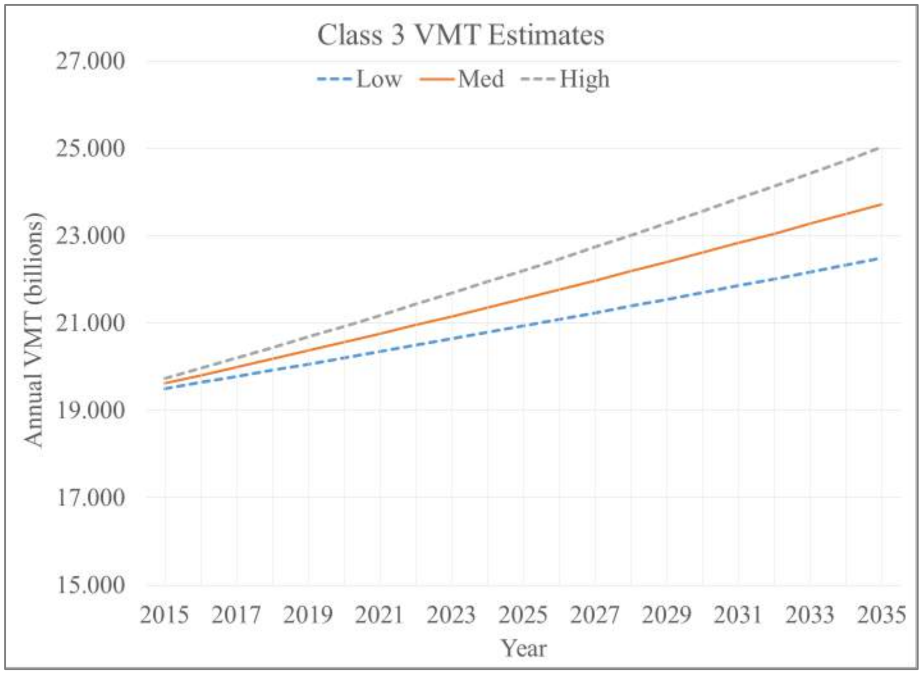

Figure 6.6 VMT growth (2015-2035) for class 3 vehicles

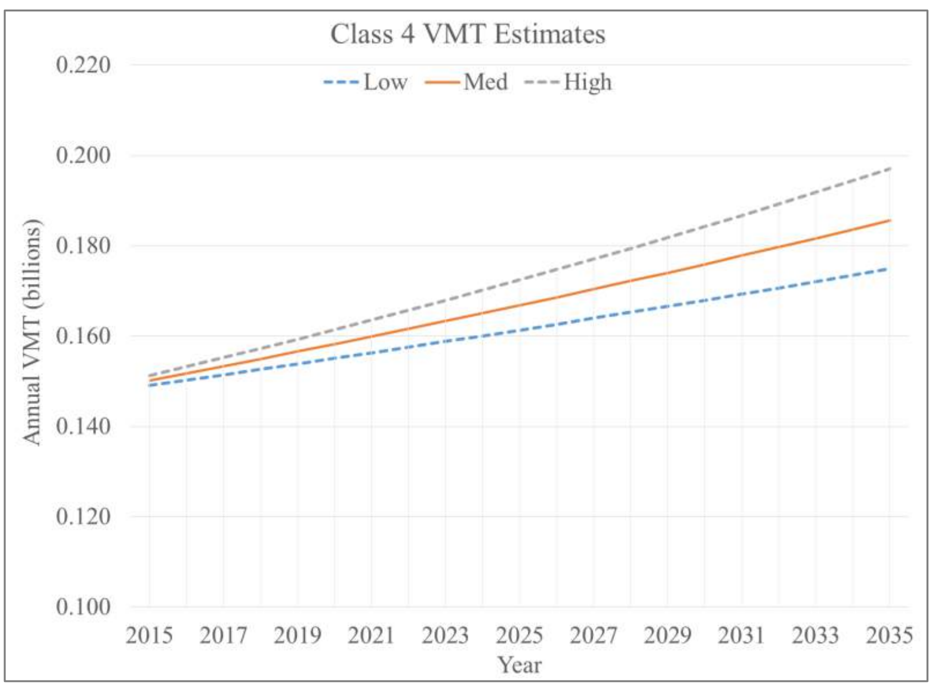

Figure 6.7 VMT growth (2015-2035) for class 4 vehicles

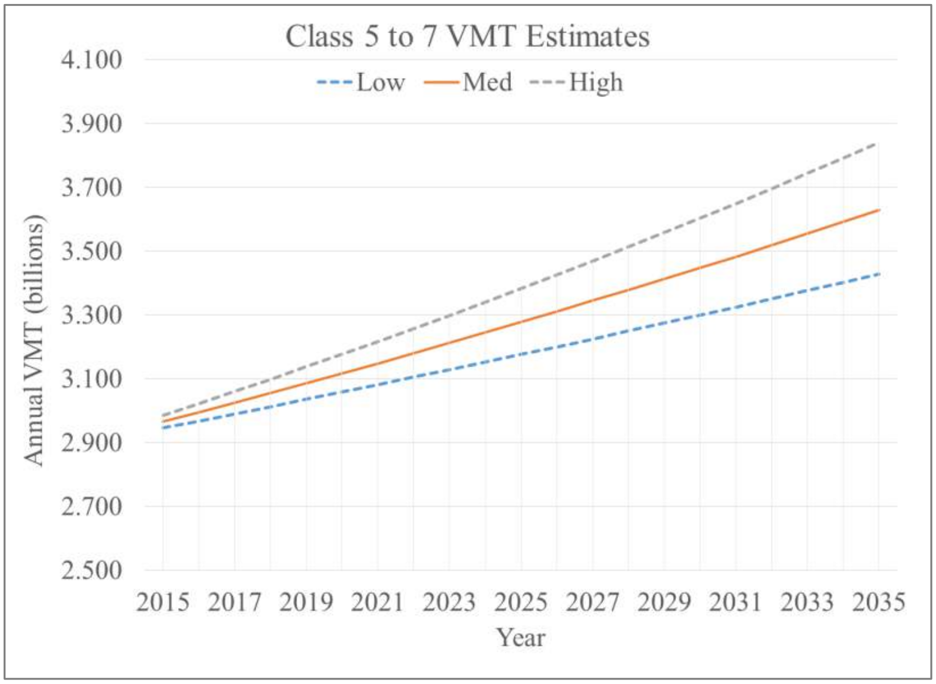

Figure 6.8 VMT growth (2015-2035) for class 5-7 vehicles

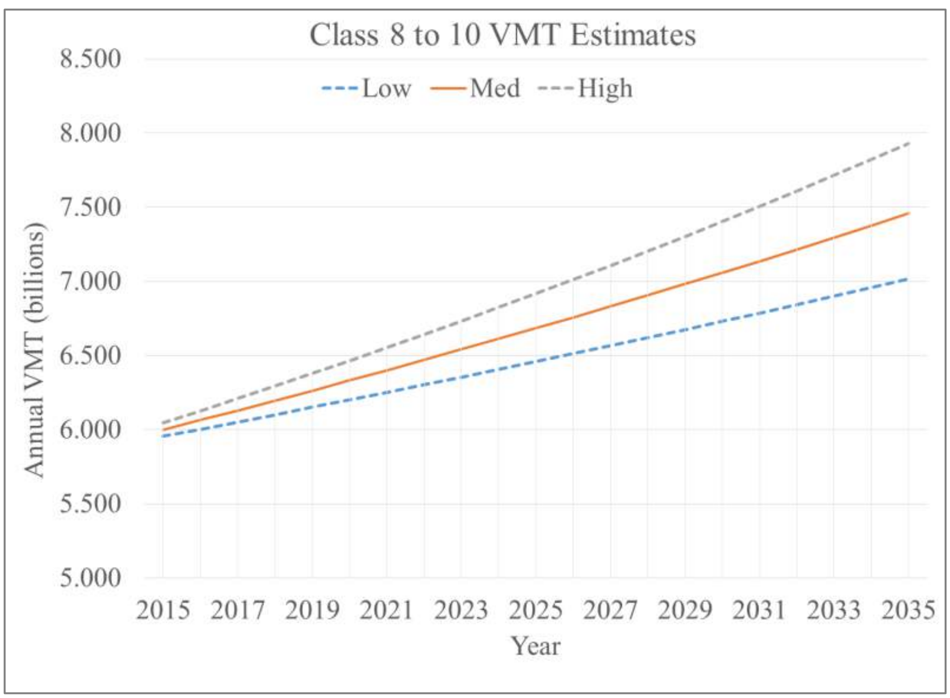

Figure 6.9 VMT growth (2015-2035) for class 8-10 vehicles

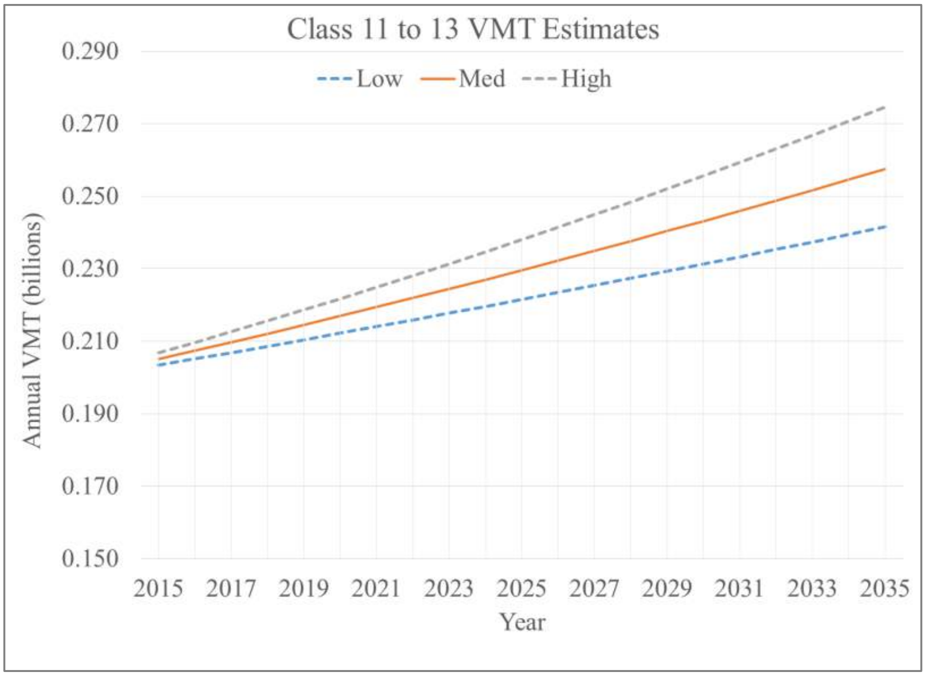

Figure 6.10 VMT growth (2015-2035) for class 11-13 vehicles

6.2 Problems Encountered

In this study, the county-level traffic sampling for local routes (using a sample of 14 counties to represent the 92 counties in Indiana) has inherent limitations. For example, it is questionable as to whether the sample obtained adequately represents the distribution of the state's rural, mixed urban, and urban counties. For rural counties, the traffic counts from the sample used to represent the 50+ counties in this cluster (rural counties) are assumed to be representative of all rural counties. Likewise, the traffic counts collected for Marion County, where Indianapolis is located, is assumed to be representative of all local roads within this region.

The estimation of section lengths, which is necessary to transform from AADT to a VMT estimate, is not directly established for local roads and therefore requires a proximity analysis in GIS to connect with the existing road network. For example, the proximity analysis often identified segments which were from intersection to intersection, but that may not be the exact representation of the traffic count. When estimating is conducted using thousands of traffic counts, an assumption must be made that the nearest road segment matching the traffic count represents the segment or link-level VMT estimate. Also, adding a new road or changing a road may not be reflected in the GIS network used for analysis. All of the above are some of the inherent limitations in the determination of segment lengths for traffic data of this magnitude; however, it is deemed to be more reliable than manual means.

Assessing non-traffic VMT estimation methods often relied on accurate and complete data, such as measures of highway travel in the FHWA *Highway Statistics*. Discrepancies were observed that prove worrisome and limit the confidence in this data for VMT estimates used in business processes. The annual mileage compiled from the NHTS is often self-reported and statistically adjusted; however, the reliability of this adjusted data may be questionable.

6.3 The Future of VMT Estimation

VMT is a dynamic performance measure of the amount of travel on the highway system within a given spatial area, with VMT linked to technology and the economy. The nature of the long-term VMT estimates developed in this research are subject to much uncertainty and provided to facilitate revenue forecasting, transportation planning, and other applications that decision-makers may face within highway management.

The future of travel in Indiana and the US depends largely on advances in technology and the current economic conditions. For example, emerging transportation technologies, such as autonomous vehicles driving on freeways, transport pods in dense urban centers, or the possibility of hyperloop trains connecting cities, are a few transportation modes which may dramatically alter the magnitude of VMT occurring in a given region. Changing modal shares, such as an increase in air travel or light-rail usage, may affect the VMT. Fluctuating oil prices may also affect the amount of travel by motorists, and subsequently VMT. This thesis provides a statewide framework which is dependent on maintaining consistent and reliable traffic counts and updated as and when available. This upkeep and maintenance increases the confidence that the VMT estimates produced more accurately represent travel conditions in the state.

6.4 Conclusions

This thesis recommends the adoption of the benchmark method (segment or link level) for statewide VMT estimation because of the high deviation observed for non-traffic methods, ranging from -21% (underestimate) to +7% (overestimate). These varying estimates may be a result of the wide range of data needs for non-traffic methods, many of which are time-intensive to collect and analyze, as well as the different assumptions required within each method. Economic swings and changing demographic conditions were observed to affect VMT and to increase the deviations obtained for each VMT estimation method. Finally, there are coverage limitations which make it impossible to conduct VMT aggregations for many requested applications (functional class, vehicle class, and spatial areas).

The framework developed for this study is implemented in a spreadsheet system, for the primary highway systems of state routes and local routes to allow for consistent and reliable VMT estimation at the segment or link level.

To ensure maximum benefit from this research, the spreadsheet should be fully managed and updated by INDOT as and when more recent data on traffic volumes and inventory become available. For example, the platform developed in this study enables easy addition of new roads or the deletion of decommissioned roads so that it accurately reflects the current inventory and travel conditions in Indiana.

6.5 Future Research

Possible future research could include comprehensive evaluation and analysis of VMT-user fees as an alternative highway funding mechanism for INDOT, which was outside the research scope, but is a critical topic considering the widening gap between highway revenue and expenditures. Also, a future research task could be to build upon the database developed in this research by implementing it with an interactive platform, such as a querying system. This system may be able to quickly provide the general public with VMT information in report form, as well as traffic statistics, depending on the application desired, such as a specific county or route. Finally, future research could further assess the reliability and integrity of the use of spatial interpolation techniques for local VMT estimation.

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APPENDICES

APPENDIX A. DEVELOPED GROWTH FACTORS

Table A.1 Growth factors for State Routes: Interstates (medium growth rate)

STATE ROUTES		FC 1 - INTERSTATES										
AGR = 1.02%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.01	1.02	1.03	1.04	1.05	1.06	1.07	1.08	1.10	1.11
	2011	0.99	-	1.01	1.02	1.03	1.04	1.05	1.06	1.07	1.08	1.10
	2012	0.98	0.99	-	1.01	1.02	1.03	1.04	1.05	1.06	1.07	1.08
	2013	0.97	0.98	0.99	-	1.01	1.02	1.03	1.04	1.05	1.06	1.07
	2014	0.96	0.97	0.98	0.99	-	1.01	1.02	1.03	1.04	1.05	1.06
	2015	0.95	0.96	0.97	0.98	0.99	-	1.01	1.02	1.03	1.04	1.05

Table A.2 Growth factors for State Routes: Principal Arterials (medium growth rate)

STATE ROUTES		FC 3 - PRINCIPAL ARTERIALS - OTHER										
AGR = 1.28%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.01	1.03	1.04	1.05	1.07	1.08	1.09	1.11	1.12	1.14
	2011	0.99	-	1.01	1.03	1.04	1.05	1.07	1.08	1.09	1.11	1.12
	2012	0.97	0.99	-	1.01	1.03	1.04	1.05	1.07	1.08	1.09	1.11
	2013	0.96	0.97	0.99	-	1.01	1.03	1.04	1.05	1.07	1.08	1.09
	2014	0.95	0.96	0.97	0.99	-	1.01	1.03	1.04	1.05	1.07	1.08
	2015	0.94	0.95	0.96	0.97	0.99	-	1.01	1.03	1.04	1.05	1.07

Table A.3 Growth factors for State Routes: Major Arterials (medium growth rate)

STATE ROUTES		FC 4 - MAJOR ARTERIALS										
AGR = 1.53%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.02	1.03	1.05	1.06	1.08	1.10	1.11	1.13	1.15	1.16
	2011	0.98	-	1.02	1.03	1.05	1.06	1.08	1.10	1.11	1.13	1.15
	2012	0.97	0.98	-	1.02	1.03	1.05	1.06	1.08	1.10	1.11	1.13
	2013	0.96	0.97	0.98	-	1.02	1.03	1.05	1.06	1.08	1.10	1.11
	2014	0.94	0.96	0.97	0.98	-	1.02	1.03	1.05	1.06	1.08	1.10
	2015	0.93	0.94	0.96	0.97	0.98	-	1.02	1.03	1.05	1.06	1.08

Table A.4 Growth factors for State Routes: Minor Arterials (medium growth rate)

STATE ROUTES		FC 5 - MINOR ARTERIALS										
AGR = 1.35%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.01	1.03	1.04	1.06	1.07	1.08	1.10	1.11	1.13	1.14
	2011	0.99	-	1.01	1.03	1.04	1.06	1.07	1.08	1.10	1.11	1.13
	2012	0.97	0.99	-	1.01	1.03	1.04	1.06	1.07	1.08	1.10	1.11
	2013	0.96	0.97	0.99	-	1.01	1.03	1.04	1.06	1.07	1.08	1.10
	2014	0.95	0.96	0.97	0.99	-	1.01	1.03	1.04	1.06	1.07	1.08
	2015	0.94	0.95	0.96	0.97	0.99	-	1.01	1.03	1.04	1.06	1.07

Table A.5 Growth factors for State Routes: Major Collectors and Locals (medium growth rate)

STATE ROUTES		FC 6 & 7 - MAJOR COLLECTORS AND LOCALS										
AGR = 3.20%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.03	1.07	1.10	1.13	1.17	1.21	1.25	1.29	1.33	1.37
	2011	0.97	-	1.03	1.07	1.10	1.13	1.17	1.21	1.25	1.29	1.33
	2012	0.94	0.97	-	1.03	1.07	1.10	1.13	1.17	1.21	1.25	1.29
	2013	0.91	0.94	0.97	-	1.03	1.07	1.10	1.13	1.17	1.21	1.25
	2014	0.88	0.91	0.94	0.97	-	1.03	1.07	1.10	1.13	1.17	1.21
	2015	0.85	0.88	0.91	0.94	0.97	-	1.03	1.07	1.10	1.13	1.17

Table A.6 Growth factors for Local Routes: City Streets and County Roads (medium growth rate)

LOCAL ROUTES		CITY STREETS AND COUNTY ROADS										
AGR = 0.74%		TO AADT YEAR										
		2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
FROM AADT YEAR	2010	-	1.01	1.01	1.02	1.03	1.04	1.05	1.05	1.06	1.07	1.08
	2011	0.99	-	1.01	1.01	1.02	1.03	1.04	1.05	1.05	1.06	1.07
	2012	0.99	0.99	-	1.01	1.01	1.02	1.03	1.04	1.05	1.05	1.06
	2013	0.98	0.99	0.99	-	1.01	1.01	1.02	1.03	1.04	1.05	1.05
	2014	0.97	0.98	0.99	0.99	-	1.01	1.01	1.02	1.03	1.04	1.05
	2015	0.96	0.97	0.98	0.99	0.99	-	1.01	1.01	1.02	1.03	1.04

APPENDIX B. PROJECT LEVEL MAPS FOR LOCAL VMT

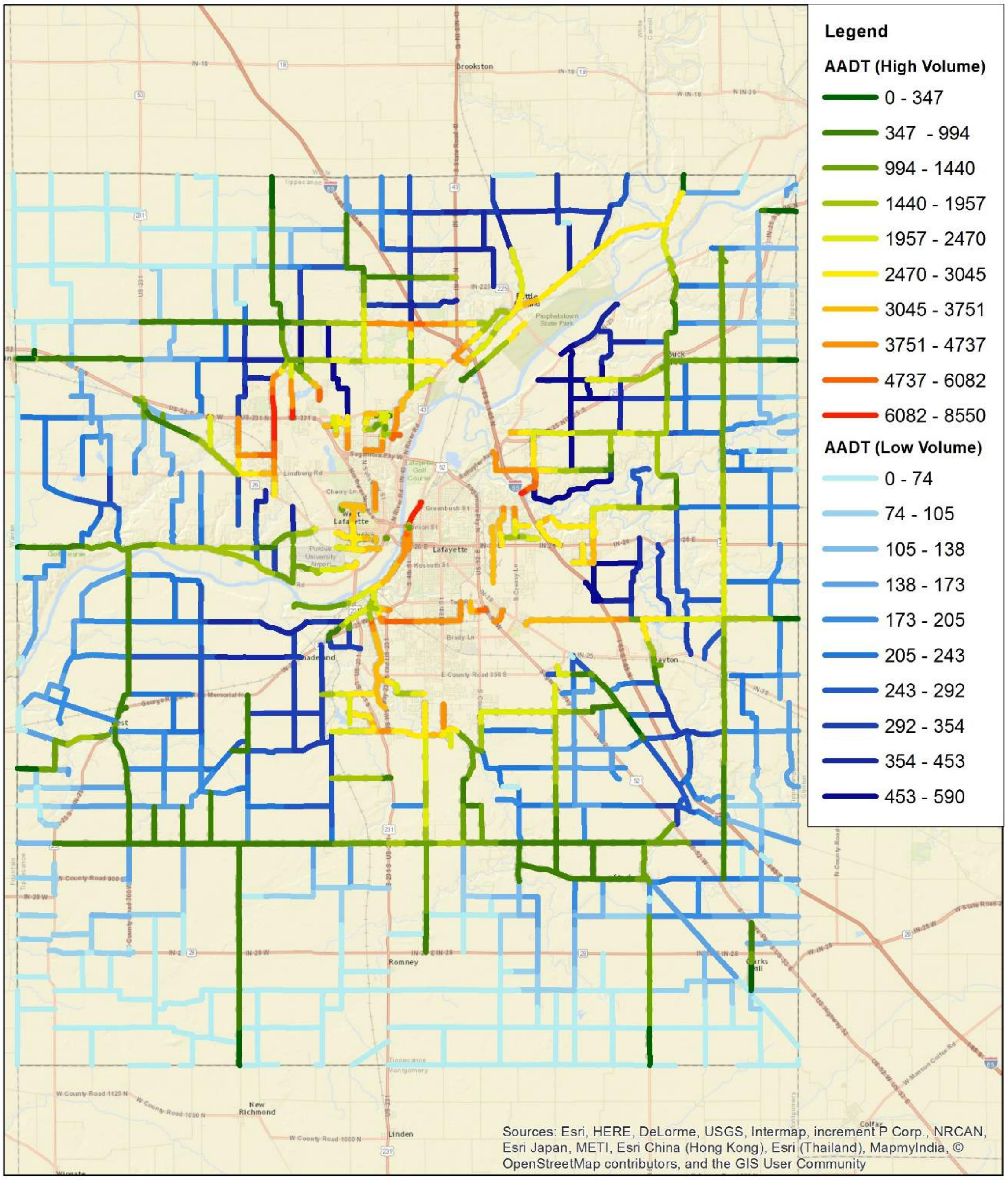

Figure B.1 County roads interpolated AADT map (Tippecanoe County) to facilitate local VMT applications at project level

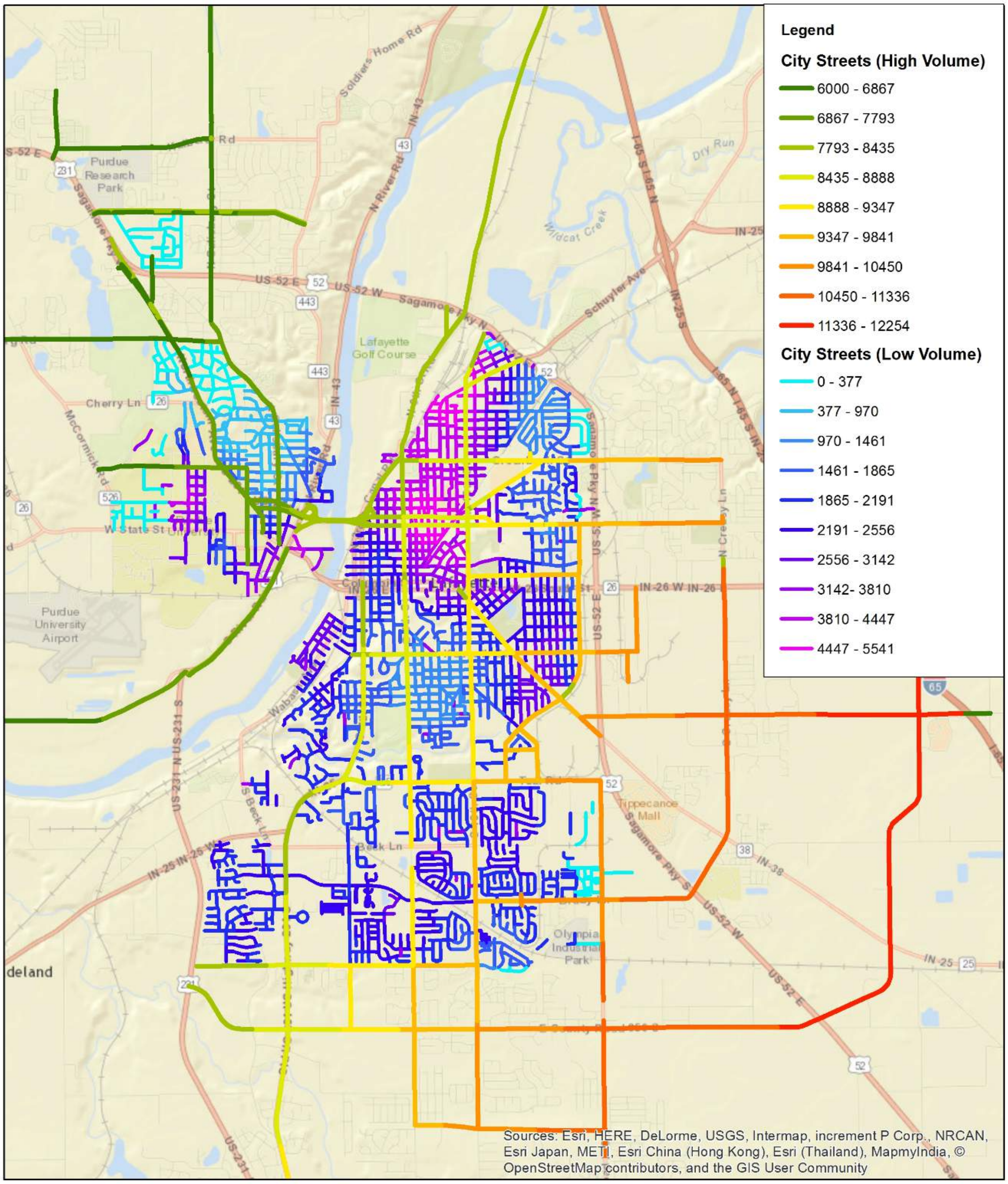

Figure B.2 City streets interpolated AADT map (Tippecanoe County) to facilitate local VMT applications at project level